RICE UNIVERSITY

# Forecasting Wind Power and Prices for Increased Revenue in the Texas Electricity Market

by

**Beth Elaine Bower**

A THESIS SUBMITTED
IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE

**Doctor of Philosophy**

APPROVED, THESIS COMMITTEE:

Katherine B. Ensor, Chair
Professor and Chair of Statistics

James R. Thompson
Noah Harding Professor of Statistics

Peter R. Hartley
George and Cynthia Mitchell Chair in Sustainable Development and Environmental Economics, Professor of Economics

Houston, Texas

July, 2010

# ABSTRACT

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This research proposes an economic model for wind farm owners and operators to predict the amount of electricity to sell to the market to optimize revenue. The model takes as inputs predictions of imbalance prices as well as probabilistic predictions of wind generation at the farm. The proposed statistical methodology improves upon current forecasting by focusing on the accuracy of predictions at extreme events. We decompose the prediction of prices into a baseline and spike component. The mixture model of a seasonal autoregressive component for the daily baseline behavior and a autoregressive conditional duration model for the extreme events, achieves a higher level of accuracy in the prediction and therefore a higher revenue to the wind farm. Through the improved predictions of price as well as a probabilistic forecast of wind output , not only can wind farms maximize revenue, but the independent system operators (ISOs), who control operations of the grid, can also better account for wind generation in the dispatch process, thus allowing wind to become a reliable source of power generation.

# Acknowledgments

First and foremost, I would like to thank my advisor, Dr. Katherine B. Ensor for her direction, guidance and assistance throughout my Ph.D. program. Without her constant support, advice and encouragement, this work would not have been possible.

I also wish to thank my thesis committee, Dr. James R. Thompson and Dr. Peter R. Hartley, for their support in my defense and dissertation process. Their commitment to my success was invaluable.

Thanks is also due to my student colleagues and friends who were there for me both in courses as well as in life.

Finally, thanks is due to my dear family for their constant and never failing support and love for me. I would not be where I am today without them.

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# Chapter 1

# Introduction

The demand for renewable energy is ever increasing. We are constantly bombarded with news about electric cars, ethanol fuel, solar panels, geothermal energy and 100% wind electricity plans. The U.S. government has proposed a bill that requires 15% of all energy produced by utilities to be renewable by 2021 (U.S. DOE Energy Efficiency and Renewable Energy, 2010). Currently, one of the most promising sources of renewable energy is wind.

Over the past ten years, the United States has seen an exponential increase in the amount of wind power generation installed in the power grid (American Wind Energy Association, 2009). Figure 1.1 shows this growth from 1995 to 2009. Along with the recent 'green energy' push has come significant monetary incentives to those wanting to invest in wind farms. Until the end of 2009, wind generation was receiving a subsidy of $20 per megawatt hour (MWh) as long as the turbines were spinning, and thus producing electricity. In addition to the subsidy, there are tax benefits and financing available for installing wind farms.

Figure 1.2 shows a map of the wind resources available to the United States. The tan areas have the least amount of wind, and the blue areas have the most. We see that the coastal regions of the U.S have the most wind, but we do notice that the central plains and Texas panhandle are also a promising area for wind energy production.

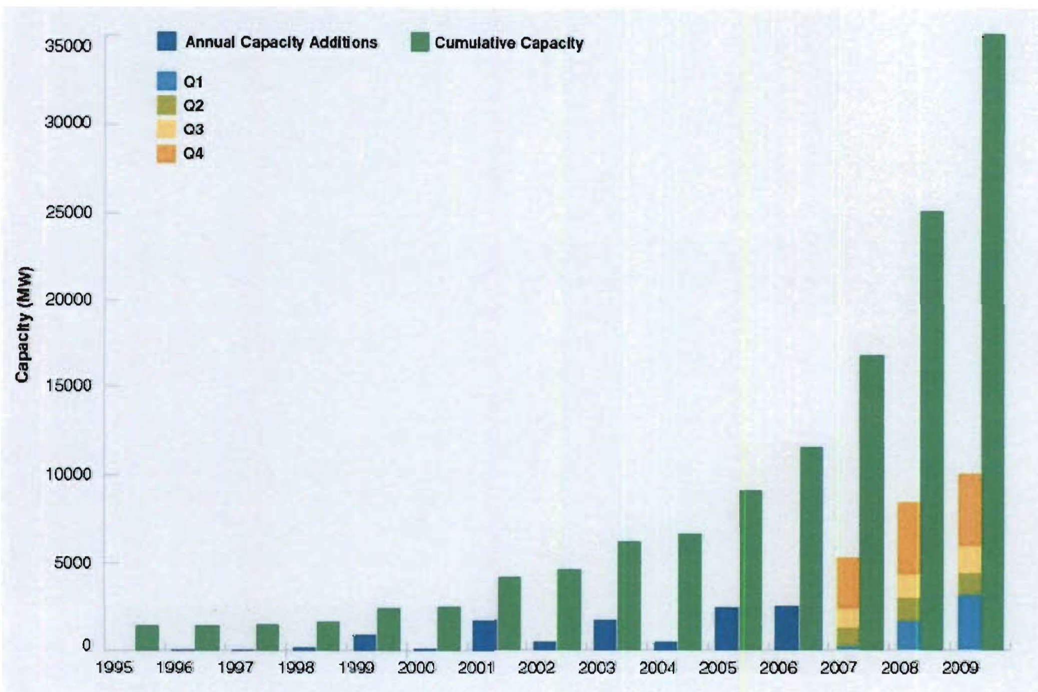


Figure 1.1 : Growth of Installed Wind Capacity. Source: AWEA U.S. Wind Industry Annual Market Report- Year Ending 2009

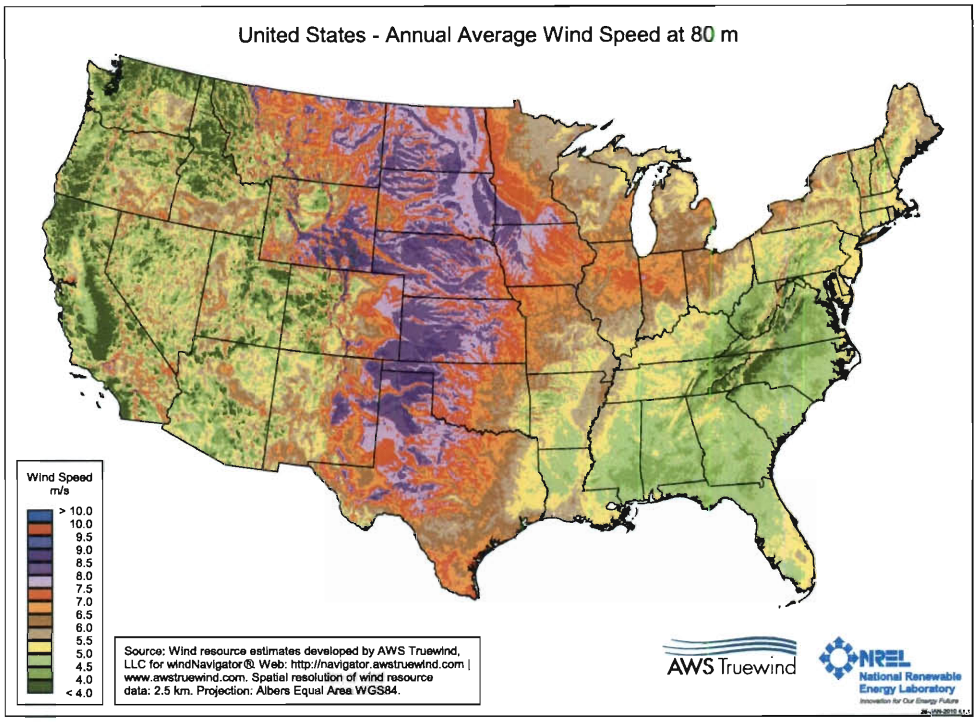


Figure 1.2 : Wind Resources in the United States. Source: U.S. Department of Energy and National Renewable Energy Laboratory (National Renewable Energy Laboratory, 2010)

Texas in particular has seen the largest growth in the installation of wind energy. Ten years ago, there was under 200 megawatts (MW) of capacity installed, and as of December 2009, there are over 9000 MW of capacity installed, or a nearly 500% increase in installed capacity. This accounts for 11.8% of totally installed electricity generation in Texas. Currently, there are plans approved for installation of over 20,000 MW of wind capacity installed by 2013 in Texas (American Wind Energy Association, n.d.). Figure 1.3 shows the distribution of wind capacity across the country.

The Texas electricity grid is unique in that it is not connected by any large transmission

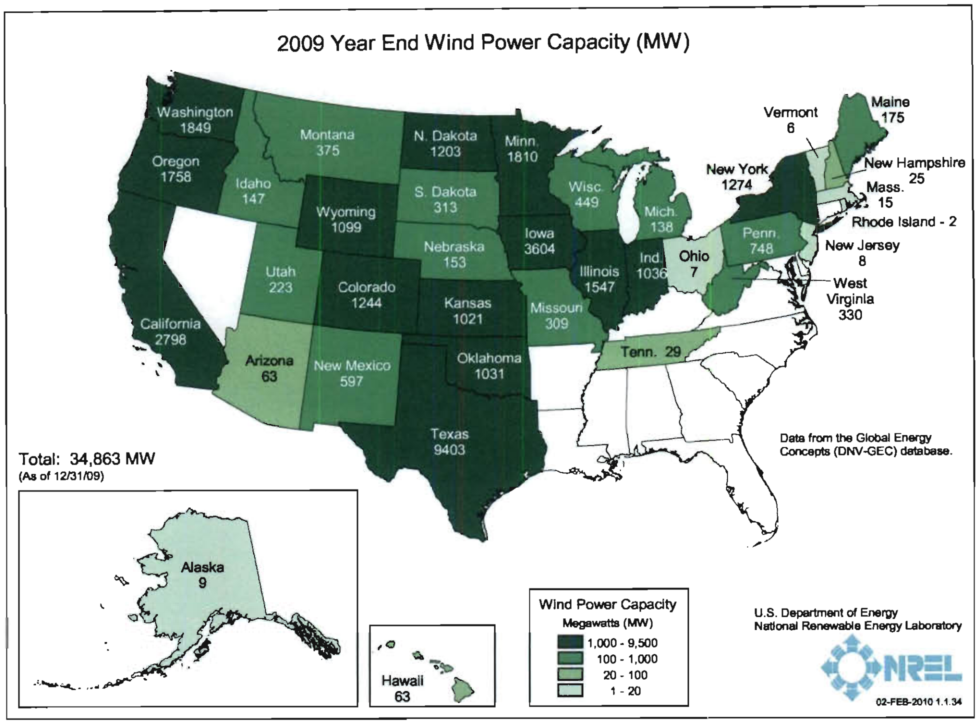


Figure 1.3 : Installed Wind Capacity as of December 31, 2009. Source: U.S. Department of Energy- The Office of Energy Efficiency and Renewable Energy (EERE) (U.S. DOE Energy Efficiency and Renewable Energy, 2010)

lines to the rest of the country, which makes it an interesting subject of research. A unique quality of electricity markets is that supply must meet demand at all times. If this does not happen, there will be blackouts. Unlike many other commodities such as oil, natural gas, metals, and agriculturals, electricity cannot be stored. It must be generated and consumed at nearly the same time. An intricate physical balance must constantly be maintained between the amount of power generated and the amount consumed. In Texas, the group that is responsible for this balance is the Electricity Reliability Council of Texas (ERCOT). The Texas grid connects more than 500 generation units and supplies power to over 22 million customers on over 40,000 miles of transmission lines (Electric Reliability Council of Texas, 2010).

In 1996, ERCOT was established as the Independent System Operator (ISO) for Texas establishing itself as the first electric utility ISO in the United States (Electric Reliability Council of Texas, 2010). ERCOT is one of ten North American ISOs/Regional Transmission Organizations (RTOs). The main goal of ERCOT is to maintain reliability of the grid. When founded, it was charged with the following responsibilities:

- System Reliability - Ensure reliability and adequacy of regional electric network;
- Open Access to Transmission - Ensure nondiscriminatory access to transmission/distribution systems for all buyers and sellers;
- Competitive Retail Market - Facilitate retail registration and switching;
- Competitive Wholesale Market - Ensure accurate accounting for electricity production and delivery among the generators and wholesale buyers and sellers in the region.

ERCOT "directs traffic" on the grid to maintain reliability and ensure the supply of electricity (Electric Reliability Council of Texas, 2010). They coordinate the scheduling of power by market participants which include generation sources and retail providers as well as third party interests. ERCOT constantly monitors the electricity grid for issues and can dispatch resources to maintain a balance of generation and load on a real-time basis. Also, due to the balance required on an electricity grid, ERCOT must manage unplanned outages or congestion of transmission and generation and have a margin to meet reliability requirements (Electric Reliability Council of Texas, 2010).

Thousands of wind turbines have a home in West Texas. On February 26th, 2008, in the heat of the afternoon, the amount of energy put into the grid by these turbines dropped by 75% over the course of 3 hours. This drop off of wind is shown in Figure 1 . This drop of nearly 1500 MW occurred coincidentally with a surge in demand and nearly caused a collapse of the Texas electricity grid. Luckily, the state had an agreement with several large industrial firms that allowed them to turn off the power when necessary in exchange for a lower electricity rate. Consumers on their way home from work were unaware of the near failure of the power grid (Charles, 2009). As is shown by the emergency event on February 26th, 2008, wind is inherently intermittent, it can die off as quickly as it begins, and this can cause the ISO to scramble to match supply to demand with an expensive, quick acting source. These quick drop offs of the wind, or the opposing quick increases in wind speed, are often called ramp events, and these ramp events can cause huge jumps in electricity prices.

Accurate prediction of wind power output enables grid operators to adjust electricity generation from more expensive and potentially environmentally damaging sources to lower cost and renewable energy sources. This in turn lowers the cost of electricity to consumers and more generally reduces the volatility of power prices. Knowledge of the dynamics of wind speeds and the power prices will enable wind power to be a key player in baseload power production and one day the majority of baseload power can be shifted

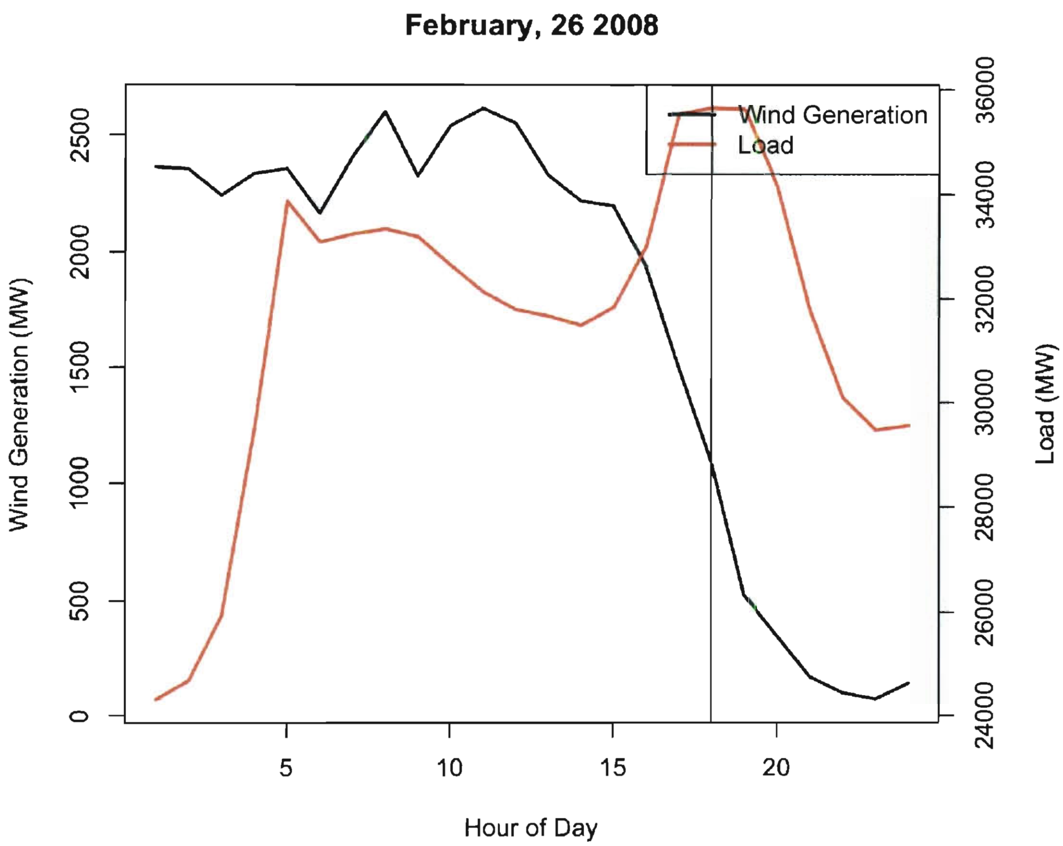


Figure 1.4 : February 26th, 2008 load and wind generation. Vertical line at 6 pm

from coal and nuclear plants to renewable energy sources. Given the event on February 26th, 2008, we see that currently, we cannot rely on wind as a base power source due to its intermittent nature.

Wind power is one of the fastest growing sources of energy in the United States as well as many European countries. While wind power has many obvious environmental benefits, there are some inherent problems in the reliability of electricity generation from wind. Wind is highly variable, and can die off as quickly as it began. Given accurate time, location, and magnitude predictions of wind, the independent system operators (ISOs) who control operations of the grid can account for the wind generation in the dispatch process, thus avoiding future near disasters.

The emergence of wind as an inexpensive, and environmentally friendly source of energy has created demand for accurate predictions of wind speed. Grid operators currently rely on day-ahead forecasts but to ensure stability of the grid, predictions of ramp events have become a primary focus. It was not until 2008, that ERCOT began forecasting wind generation in order to better help maintain the reliability of the grid. Although large ramp events are rare, such as the West Texas event previously described, accurate forecasts of wind speed or wind generation can be extremely useful to grid operators in their management of the grid (Francis, 2008).

By improving the accuracy of the prediction of wind output, including those times when the wind increases or decreases quickly, we can improve the dispatch system of an electricity grid and allow wind power to become a viable electricity source. Improvements in wind output prediction are also vital to the wind power producer. These forecasts allow the producer to bid an accurate amount of electricity into the grid which will in turn provide stability to the grid. Thus, the first goal of this work is to decrease the prediction error in wind power output.

As the installed wind capacity has increased, ERCOT has been faced with the fact that the installed wind has caused an increase in the variability of electricity prices. These prices are especially volatile around ramp events. Prediction of the market clearing price of energy (MCPE) is important for wind generators because they need to know at what price to sell their electricity. Also, if they contract to sell too much (too little) electricity, they are subject to fees that are a function of the MCPE. Therefore, the second goal of this work is to decrease the prediction error in MCPE.

This dissertation explores the prediction of wind power generation as well as price prediction. We incorporate the two sets of forecasts into an economic model that produces the quantity of electricity that a wind farm should sell in order to maximize revenue. Chapter 2 provides background on wind power, its prediction as well as the challenges associated with prediction of wind speed and wind power generation. We then develop a probabilistic forecast of wind power for Texas wind plants. In Chapter 3 we introduce the prices associated with power in Texas, and a review of methods available to predict future prices. These prices have a direct relationship with the costs associated to an imbalance of supply and demand on the power grid. We develop a mixture model for prices in West Texas in order to more accurately predict price spikes as well as typical behavior. With the combination of a probabilistic forecast of wind power generation and a forecast of prices, Chapter 4 combines the two in an economic model of revenue maximization to determine the amount of wind energy that should be bid in the market. Finally, we finish with a few conclusions in Chapter 5, and talk about future work.

# Chapter 2

# Wind Power

## 2.1 Background

Power generation from wind is attractive for several reasons. One reason is that the fuel that powers wind turbines , wind, is free. Excluding the initial investment of building and installing the wind turbine, and the maintenance costs, when the wind blows, electricity is generated for a cost of $0. Another reason that wind generation is popular is that it is a renewable resource. Conventional generation such as nuclear power, coal power, and natural gas power plants use fuel to create electricity, and when we burn the fuel to create electricity, we are depleting the world's supply of that fuel. The supply of wind to power turbines is not depleted when we create power from wind. Along with being a renewable resource, wind does not create environmental pollutants when turned into electricity. With government policies mandating a decrease in carbon dioxide emissions, an increase in wind generation may help to offset the use of coal fired plants.

If wind farms are installed in different geographic regions of the grid the reliability of electricity generated from wind will be improved. If all wind farms are located in one region, and the wind stops blowing, we lose all generation from wind energy, whereas, if the wind farms are scattered in different regions that are known to have wind resources, if the wind stops blowing in one location, chances are the wind will still be blowing in another location (National Renewable Energy Laboratory, 2010). Wind generation works best when there are other more traditional sources of generation in the same area that are able to respond to changes in wind generation and balance generation levels with demand levels.

Texas in particular has an enormous potential for wind power generation. Figure 2.1 shows the average wind speeds in Texas. We note that in the panhandle area of texas we see wind speeds in excess of 8.0 m/s.

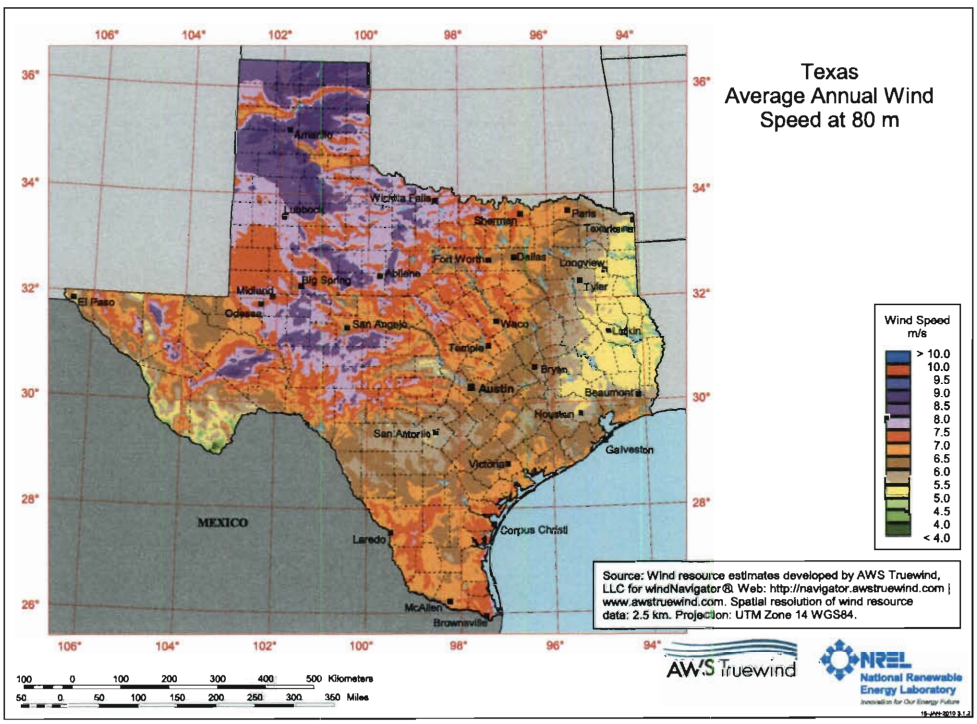


Figure 2.1 : Texas Wind Resources. Source: U.S. Department of Energy- The Office of Energy Efficiency and Renewable Energy (EERE) (U.S. DOE Energy Efficiency and Renewable Energy, 2010)

It is apparent that producing electricity from wind has many benefits, but there are several negative issues that come with wind power generation as well. It is expensive to install the transmission network necessary to move the wind power generated from remote areas to load centers. It is more difficult to control, dispatch and predict wind energy than traditional forms of generation. Running a coal plant or a nuclear plant will create a steady stream of electricity until you turn off the power plant (or a rare unplanned event occurs) but electricity that is generated from a wind farm is subject to when the wind blows (U.S. DOE Energy Efficiency and Renewable Energy, 2010). Wind turbines also negatively impact wildlife such as migratory birds and bats. The turning of the turbines can also be extremely noisy and thus it is undesirable to have a turbine near population centers.

The introduction of wind power into the current electricity grid requires additional reserve generation in order to guarantee reliability of the grid (Ummels *et al.* , 2007). "Large-scale integration of wind power in the electricity system presents some planning and operational difficulties, due mainly to the intermittent and difficult-to predict nature of wind, which is, therefore considered an unreliable energy source" (Fabbri *et al.* , 2005).

A grid operator cannot demand that a wind turbine provide electricity at any given time, and thus cannot dispatch wind in the same manner as traditional generation. This poses an interesting challenge to grid operators when modeling and managing grid operations. One such challenge is the scheduling of transmission outages and construction. Generally outages are planned for off-peak periods of demand so that there is not an interruption of service, but off-peak demand periods of demand coincide with on-peak wind power generation (National Renewable Energy Laboratory, 2010). Figure 2.2 shows the imbalance between the load on the ERCOT system with the times when we have the most generation from wind farms. We see that when load is the highest, we do not have sufficient power generation from wind, and when we do not have high demand (for example, the middle of the night), we have an oversupply of wind generation. Another item of note is that we often see that as load ramps up, our wind generation ramps down, causing a strain on the power grid. We must incorporate wind generation into the decision making process.

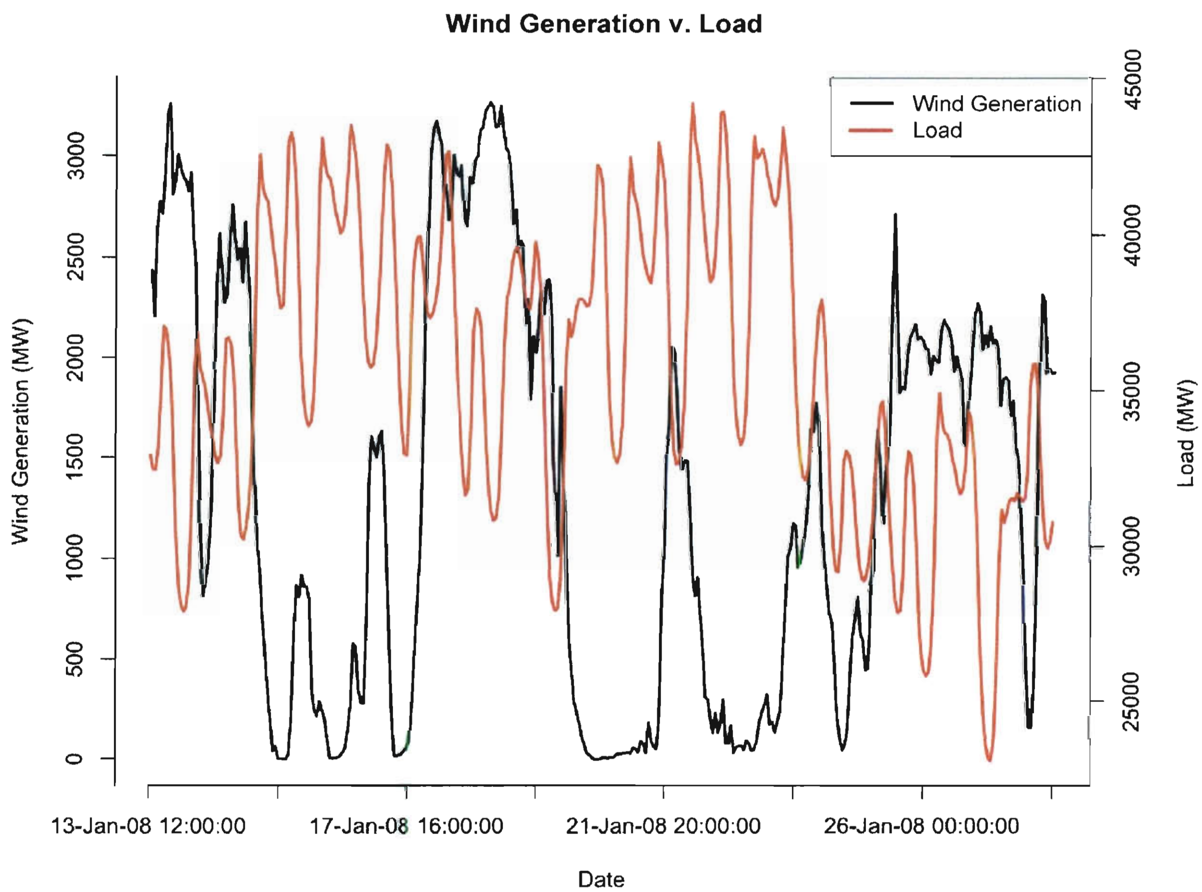


Figure 2.2 : ERCOT Load v. Wind Generation

In addition to incorporating wind into the decision making process of the grid operator, there is the challenge of forecasting the amount of wind generation at a future point in time. Wind speed has several unique characteristics that make forecasting challenging. Wind speed is nonnegative and non-normally distributed. The wind speed time series is temporally and spatially correlated. This means that wind speeds are correlated with past wind speeds, and that wind speeds in one location are correlated with wind speeds in another sufficiently close location. The spatial correlation is due to weather patterns being similar in nearby locations. It has diurnal and seasonal changes. It changes rapidly and with high frequency. Speed is highly correlated with wind direction (Hering & Genton, 2008).

Numerous methods have been introduced to forecast wind speed. Developed methods include time series models, numerical weather prediction models, probabilistic models, data mining models, regression models, risk models, and extreme value theory models. They can be divided into two categories. The first is a physical model, which takes into account the physics of the earth's rotation, atmospheric conditions, and weather patterns to determine the best prediction. These models are known as Numerical Weather Prediction models (NWP). The second category is statistical methods (Lei *et al.* , 2008). The physical methods have advantages in long term prediction of wind speed, while statistical models tend to perform better in short term prediction (Liu *et al.* , 2010). We focus on the second category in this dissertation.

Forecasting models all have a set of variables as inputs. For a physical model, the inputs are typically meteorological such as terrain, roughness, obstacles, atmospheric measurements, etc. For a statistical time series model, historical data on wind speeds (and possible other weather covariates such as temperature, air pressure, and wind direction) or wind generation at wind farms is used to predict future patterns. If using a spatial method, you also need the historical data at surrounding wind farms. One also needs the power curve of wind turbines for the forecasting of wind power.

There have been many studies using wind speed time series. They began in the early 80's with Monte Carlo methods to generate simulations of wind speeds assuming known parameters of the wind speed distribution (Torres *et al.* , 2005). Following those studies, in 1981, Chou and Corotis where able to include the effect of autocorrelation in their model of the wind speed time series (Chou & Corotis, 1981). Futher methods began to include the non-Gaussian nature of the wind speed distribution as well as the AR component inherent in wind speeds. In 2004, Bremnes introduced local quantile regression (LQR) as a method to predict wind power. Instead of using a method that provides a deterministic prediction, the author demonstrates that LQR includes information about the uncertainty of future production. The LQR method has several nice properties. First, there are no distributional assumptions made and second, it can include predictive variables such as wind direction and temperature (Bremnes, 2004). Torres et al. model wind speed time series from 5 locations in Spain. They utilize ARMA models and persistence models (models that set the wind speed at the previous time point as the the prediction of the wind speed at the next time point) to evaluate predictions of wind speeds from 1 to 10 hours in advance. The authors find that they must transform and standardize the time series in order to overcome non-stationarity. Due to the seasonal nature of wind, the authors fit a different model to each calendar month (Torres *et al.* , 2005). Torres et. al find that for short term predictions, an ARMA model has a lower root mean squared prediction error than persistence models. In (Riahy & Abedi, 2008), the authors develop a linear prediction method for the forecasting of wind speeds based on past observations of the wind speed. The linear prediction method fits a linear differential equation to a time series, or in other words, the prediction is a linear combination of the present and past wind speeds where the weights vary over time periods. They show that using this prediction method on a smoothed version of the wind speed one can predict wind speeds 5 seconds ahead with near perfect accuracy. This method has high prediction accuracy for very short term time horizons, but has limitations in that it smooths the wind speeds and thus is less desirable when converting to wind generation (Riahy & Abedi, 2008). (Costa *et al.* , 2007) analyzed wind speed time series using a Kalman filter approach. The Kalman filter allows for prediction of the state of the wind speed (low speeds, high speeds) as well as the wind speed.They show that for hourly data, the persistence method does better than a Kalman filter model, but for 5 minute data, the are able to achieve lower error with the Kalman filter model (Costa *et al.* , 2007). Rather than smoothing the wind speed time series, (Liu *et al.* , 2010) implement a wavelet transform of the time series to decompose the series into three subseries, a high frequency subseries, a medium frequency subseries and a low frequency subseries. The authors then fit an ARIMA model to each subseries, predict each subseries separately and finally aggregate the predictions to a form a prediction of the series as a whole.

Power generated by wind turbines has an intimate relationship with wind speeds (Lei *et al.* , 2008).The prediction of wind power or generation can be studied via prediction of wind speed through a wind power curve. A wind power curve is a curve that is published by a turbine manufacturer which explains the mathematical relationship between wind speed (usually in m/s) and the amount of power that will be produced (in KW or as a percentage of maximum rated capacity). One example curve is shown in Figure 2.3. Each turbine has its own power curve and these curves are established relationships that can be used to go between predictions of wind speed and predictions of wind power.

The power that can be produced from wind is a nonlinear function of the wind speed, thus it is important to predict not only the average wind speed at a future point in time, but also to predict the distribution of the wind speeds at that point (Haslett & Raftery, 1989). The reliability of wind power is not satisfactory because it cannot supply a steady stream of electricity to the power grid. But, due to the push on environmental policy towards renewable energy, the wind power penetration has grown and will continue to grow while the government provides a subsidy to wind farm owners (Lei *et al.* , 2008). In order to increase the wind power penetration and decrease the reserve capacity required on a power system, we need accurate forecasting of wind speed.

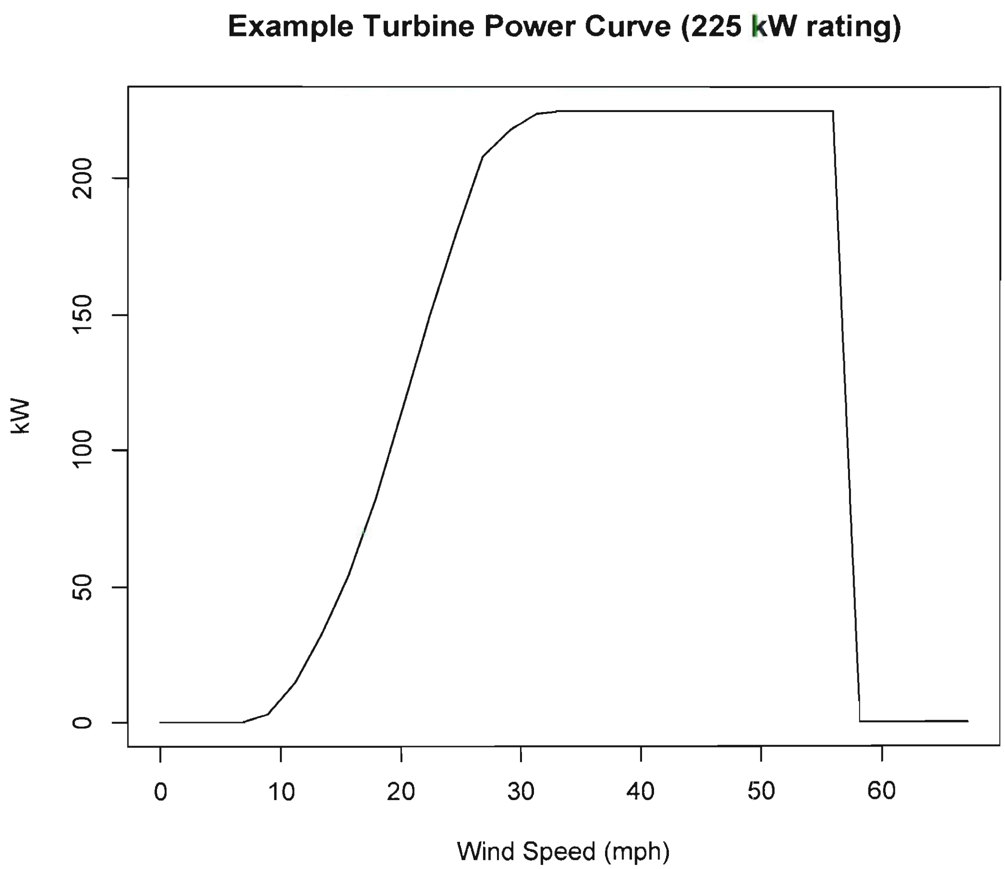


Figure 2.3 : Sample Turbine Power Curve

### 2.1.1 Ramp Events

Ramp events are events in which the wind generation either dies off or picks up more than some determined percentage over a short period of time. These event are important to keep in mind while developing prediction models of wind generation.

Ramp events can be the result of two different types of wind speed changes. The first is at ramp up, where quick large changes in wind speed result in quick large changes in wind power output. Secondly, at high wind speeds, a small increase can cause a shut down of the wind turbine causing a ramp down event (loss of power production). The ability to accurately forecast ramp events is imperative to the integration of wind into the current power grid. Given accurate forecasts, grid operators can schedule alternative sources of energy so that there is a constant match of supply and demand (Greaves *et al.* , 2009).(Greaves *et al.* , 2009) define a ramp event as a change in power of 50% of capacity over the course of less than or equal to 4 hours.

Cutler et. al. develop a methodology to detect ramp events, and then use the Mesoscale Limited Area Prediction System (MesoLAPS) and Wind Power Prediction Tool (WPPT) numerical weather prediction tools to forecast wind speeds. They calculate a RMSE to compare the two prediction systems. They use data from the 65 MW Roaring 40s Renewable energy P/L Woolnorth Bluff Point wind farm in Australia. The authors show that the two numerical weather forecasting tools do a good job in predicting wind speeds over the course of a year, but when we focus on ramp events, we see that the models fall apart (Cutler *et al.* , 2007). This finding supports the need for accurate forecasts of wind power ramp events, not only predictions of wind speed.

Palutikof et al. (1999) review extreme value theory methods for their potential use in modeling extreme wind speeds. The authors conduct a cursory review of annual maxima, independent storms, r-largest extremes and peaks over threshold methods. There is mention of common methods to obtain parameters of the distributions as well as the conditions the data must meet in order to consider extreme value theory in the first place. Finally, the authors introduce a Monte-Carlo simulation technique in order to measure the return period extreme. One obvious problem with these methods is that they require independent identically distributed ($iid$) extremes, and if we are to focus on ramp events, there is a relatively high probability that our events are not $iid$. If we observe a gust of wind, there may be a ramp up, immediately followed by a ramp down. These events were both then caused by the same observed wind gust (Palutikof *et al.* , 1999).

The Gumbel distribution is the most commonly used distribution for wind speed extremes. But, perhaps the most important factor when deciding on an extreme value theory method is the length of data available for analysis. Peaks over threshold and r-largest order statistic methods have the advantage of using more data, thus lowering standard errors. These methods require threshold decisions to be made by the analyst and can have a significant effect on the final outcome (Palutikof *et al.* , 1999).

This dissertation focuses on analyzing the entire ERCOT market so that ramp events are not a critical featured addressed. However, ramp events would be important if we were to apply the same analysis to a single wind farm, which we mention in Chapter 5.

## 2.2 Data Description

ERCOT began recording hourly wind generation in 2007. The data is hourly aggregate production from all wind farms on the ERCOT grid. Beginning in 2009, ERCOT now records the data by hub on the grid, or for many different locations on the grid. They still only provide hourly generation values. The data is available, for research purposes only, on the ERCOT planning and operations website.

We model the wind generation as a wind capacity factor which is defined as the realized amount of power produced over time divided by the amount of power that would have been produced if the plant were operating at maximum output 100% of the time.

Figure 2.4 shows boxplots of the wind capacity factor by month for the year 2008. We note that the wind capacity factor is highest in the winter and spring months, and lowest in the summer and fall months. This means we generate more wind power in the winter and spring than in the summer and fall. Interestingly, we see that the highest wind capacity factor occurs in summer which may be explained by a front moving in for a strong summer storm. Because of these seasonal fluctuations we standardize our data by the monthly mean and standard deviation of the capacity factor. Table 2.1 shows the month means and standard deviations.

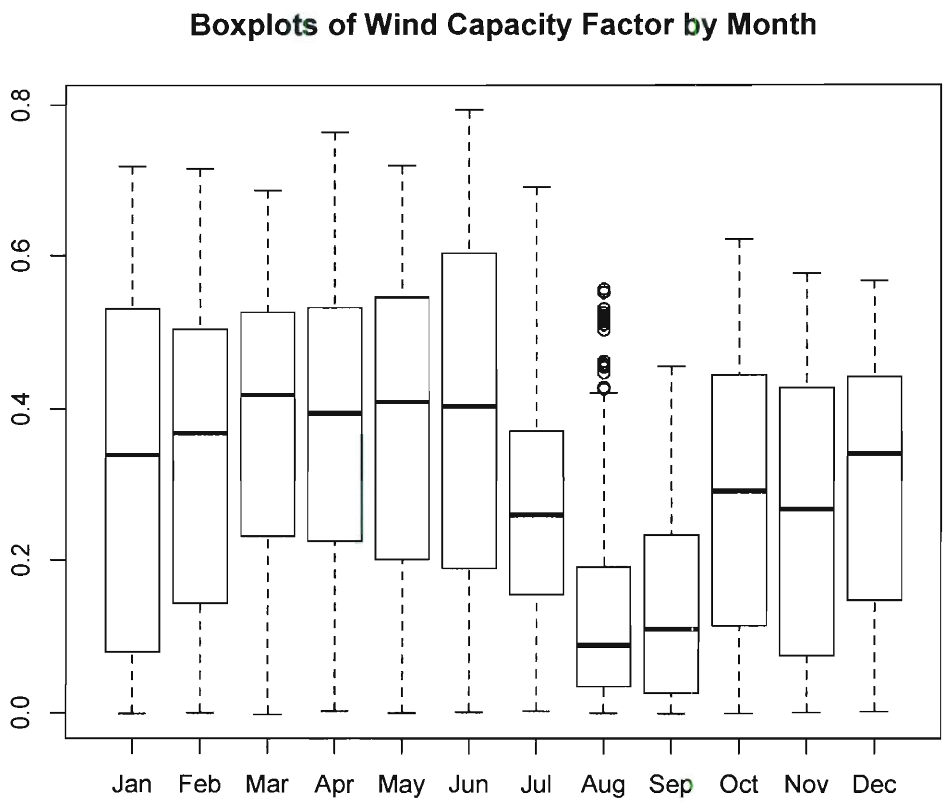


Figure 2.4 : Boxplots of wind capacity factor by month

| Month | Mean | Standard Deviation |
|---|---|---|
| Jan | 0.3207 | 0.2259 |
| Feb | 0.3341 | 0.2014 |
| Mar | 0.3748 | 0.1803 |
| Apr | 0.3743 | 0.1978 |
| May | 0.3736 | 0.2020 |
| Jun | 0.4010 | 0.2335 |
| Jul | 0.2694 | 0.1557 |
| Aug | 0.1308 | 0.1235 |
| Sep | 0.1402 | 0.1225 |
| Oct | 0.2816 | 0.1817 |
| Nov | 0.2617 | 0.1806 |
| Dec | 0.2995 | 0.1629 |

Table 2.1 : Monthly mean and standard deviation of Wind Capacity Factor

## 2.3 Model

### 2.3.1 Model Definition

We model the wind generation capacity factor for ERCOT. When we model the wind generation of the entire grid, we do not observe the ramp events that occur at individual farms. This means that we can model the series using a traditional time series model. We employ a seasonal autoregressive moving average model (seasonal ARMA) model to describe the behavior of ERCOT wind capacity factor so that we are able to capture the autocorrelation in the data as well as daily seasonal patterns in wind output.

The seasonal ARMA model is denoted $ARMA(p,q) \times (P,Q)_h$ where $p$ is the number of autoregressive (AR) terms, $q$ is the number of moving average (MA) terms, $P$ is the number of seasonal AR terms, $Q$ is the number of seasonal MA terms, and $h$ is the period of the seasonality.

Let us define the standardized wind capacity factor at time $t$ as $W_t$. Then,

$$\Phi(B^h)\phi(B)(W_t) = \Theta(B^h)\theta(B)\epsilon_t \tag{2.1}$$

where $\epsilon_t$ is assumed to be an independent and identically distributed random variable where $\epsilon_t \sim N(0, \sigma^2)$, and $B$ is the backshift operator. In other words, $B^i W_t = W_{t-i}$. Then we define,

$$\Phi(B^h) = 1 - \Phi_1 B^h - \Phi_2 B^{2h} - \ldots - \Phi_P B^{Ph} \tag{2.2}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_P B^p \tag{2.3}$$

$$\Theta(B^h) = 1 - \Theta_1 B^h - \Theta_2 B^{2h} - \ldots - \Theta_Q B^{Qh} \tag{2.4}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q. \tag{2.5}$$

### 2.3.2 Model Fitting and Parameter Estimation

In order to estimate the parameters of our model, we split our 2008 time series into a training and a test set. Our training set is the first 70% of our data, and our test set is the latter 30% of our data, so that we have 6,149 data points in our training set, and 2,635 in our test set. Figures 2.5 and 2.6 show the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the thresholded training wind capacity factor series. Noticeably, the ACF has a seasonal pattern which shows up as a increase in autocorrelation at lags of multiples of 24. This is our daily seasonal pattern that we suspected existed in the data (there are 24 data points in a day). Note that we also see a spike in the PACF on the lags of multiples of 24.

We use an ARMA $(2, 0) \times (1, 0)_{24}$ to account for the daily seasonality. This means we have two AR terms and one seasonal AR term. We do not include any moving average terms in the model. We can then write our model explicitly as

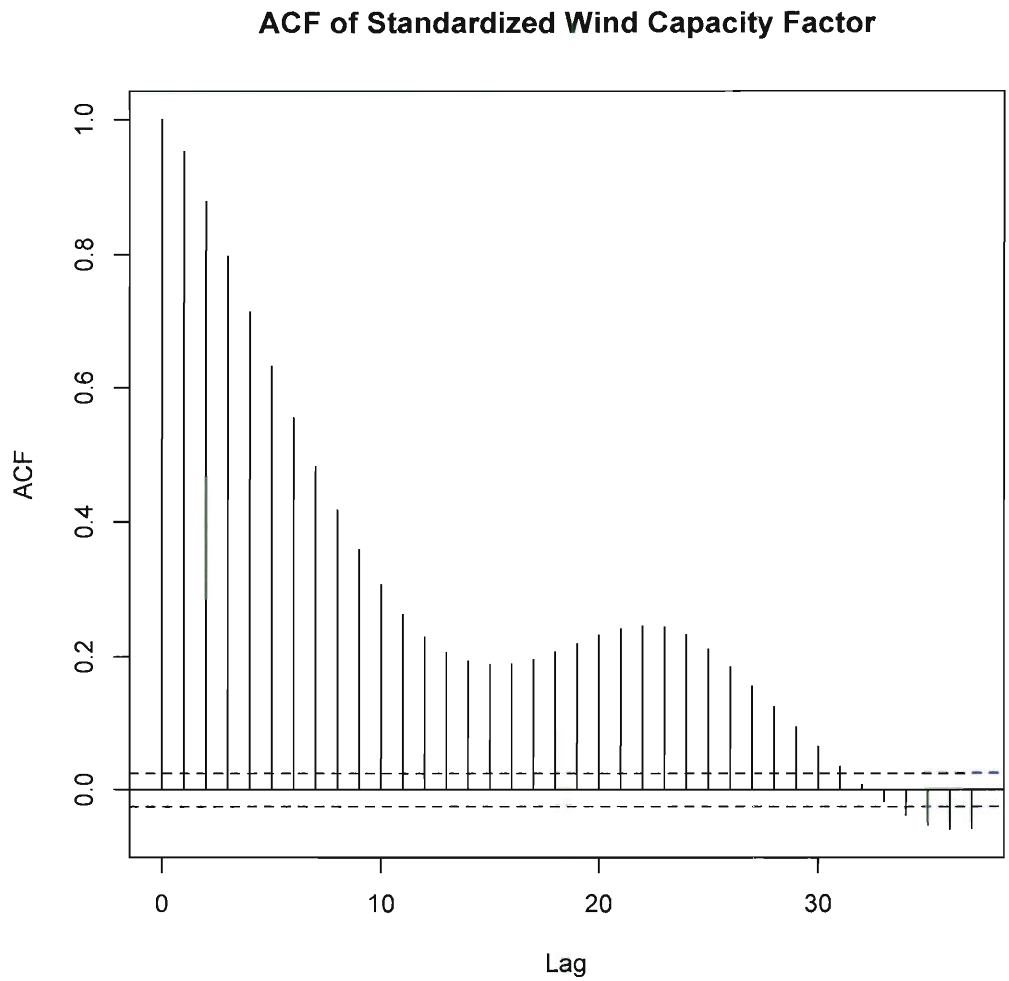


Figure 2.5 : Autocorrelation Function of Training Wind Capacity Factor Series

$$\Phi(B^{24})\phi(B)(W_t - \mu) = \epsilon_t, \tag{2.6}$$

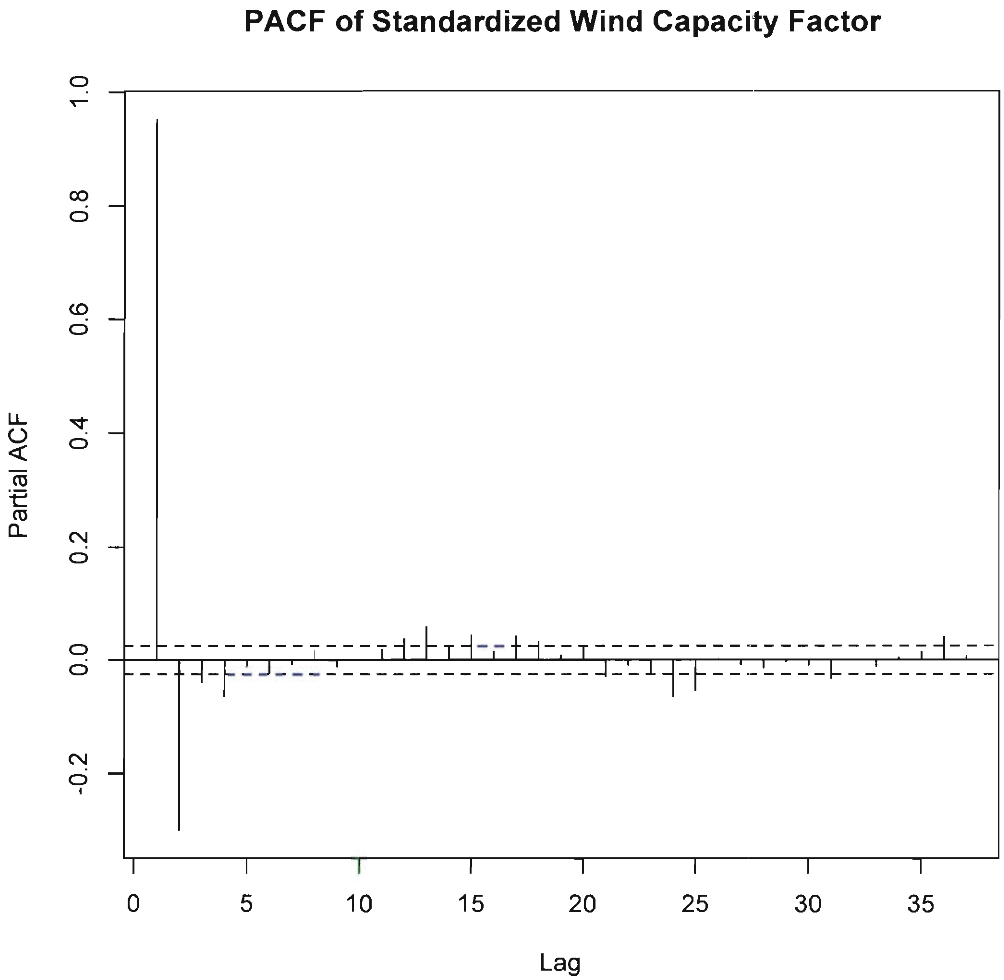


Figure 2.6 : Partial Autocorrelation Function of Training Wind Capacity Factor Series

where,

$$\Phi(B^{24}) = 1 - \Phi_1 B^{24}, \tag{2.7}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2. \tag{2.8}$$

When we fit our model to the training data set, and report the estimates in Table 2.2.

| | $\phi_1$ | $\phi_2$ | $\Phi_1$ | $\sigma^2$ |
|---|---|---|---|---|
| Estimate | 0.8288 | 0.0707 | 0.4270 | 0.0855 |
| Standard Error | 0.0319 | 0.0320 | 0.0254 | .0216 |

Table 2.2 : Estimated coefficients of $ARMA(2,0) \times (1,0)_{24}$ model.

Figure 2.7 shows the in sample fit of the ARMA. We appear to fit well, but in order to determine the quality of fit, we will forecast the remainder of the year, using one step ahead predictions.

## 2.4 Results

We perform one step ahead predictions for the remainder of the 2008 year, and plot the predictions along prediction limits. Figure 2.8 shows our predicted hourly wind capacity factor.

The prediction appears to do well, but we need to compare our method of prediction in order to determine how much our prediction improves on another prediction method. A commonly used comparison prediction method for wind capacity factor is the persistence method. The persistence method uses the previous wind capacity as the forecast for the next wind capacity, or better described as random walk. This method performs surprisingly well. The model can be explicitly written as

$$W_t = W_{t-1} + \epsilon_t. \tag{2.9}$$

Our model as described in Section 2.3 has a mean squared prediction error of 0.0498.

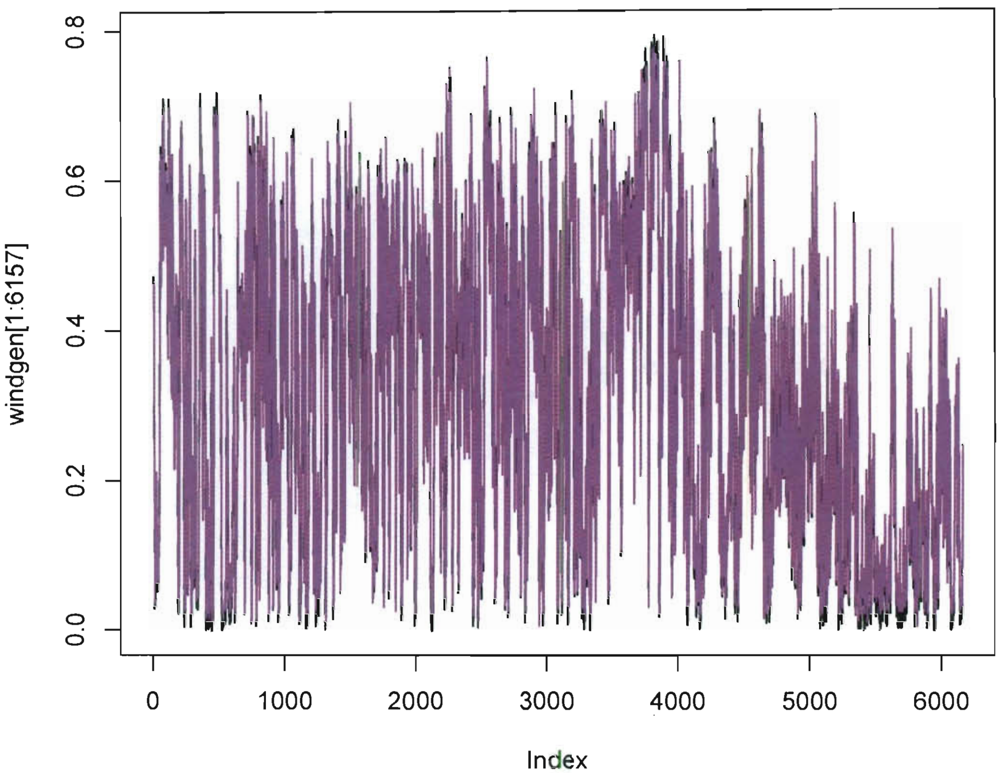


Figure 2.7 : Seasonal ARMA Fit

When we predict prices using the persistence model, we have a mean squared prediction error of 0.0713. Figure 3.12 shows boxplots of the prediction errors of the seasonal ARMA model and the persistence models. We achieve a modest improvement in the RMSE, and our proposed model is not any more challenging to code and run than the persistence model so we will use the seasonal ARMA model.

Figure 2.10 shows that our predictions using the two different methods lie or near a straight line. This means that the predictions from the two methods are very similar when

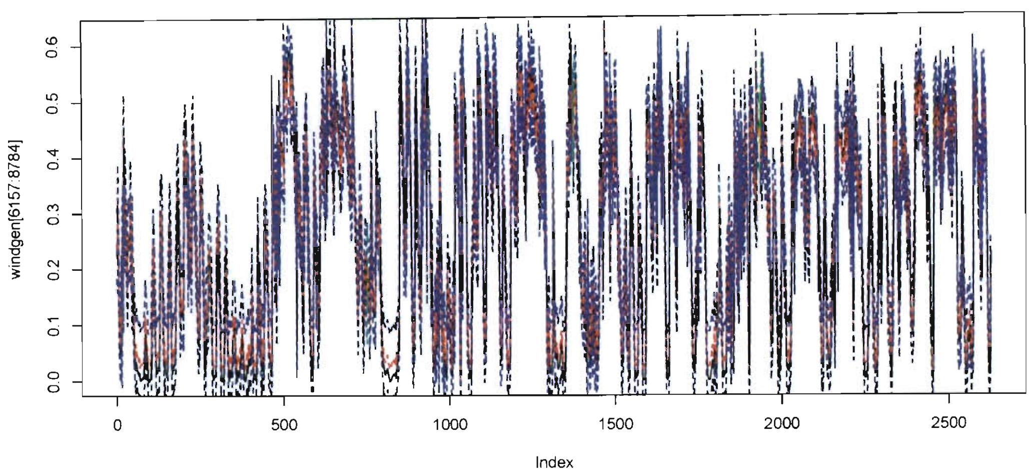


Figure 2.8 : Seasonal ARMA Predictions. The red dashed line is the prediction, the black line is the actual observations and the blue lines are the 25% and 75% prediction intervals.

the predictions lie on the line, and the further away from the line the points are, the more different the predictions are between the two methods.

Modeling not only the mean of future wind generation, but rather a distribution of the future wind generation gives ERCOT a better of idea how much wind to expect in the system. It allows wind farm owners to better plan the sale of electricity from wind as well. The seasonal ARMA model allows easy calculation of prediction intervals which gives us an idea of the distribution of the prediction.

The accuracy of the prediction of wind speed or wind generation is highly important to not only wind farms but also the grid operators. Higher accuracy of wind prediction will ultimately allow wind to become a more important resource in the Texas electricity grid. "With the increased percentage of the system load served by wind, it becomes critical

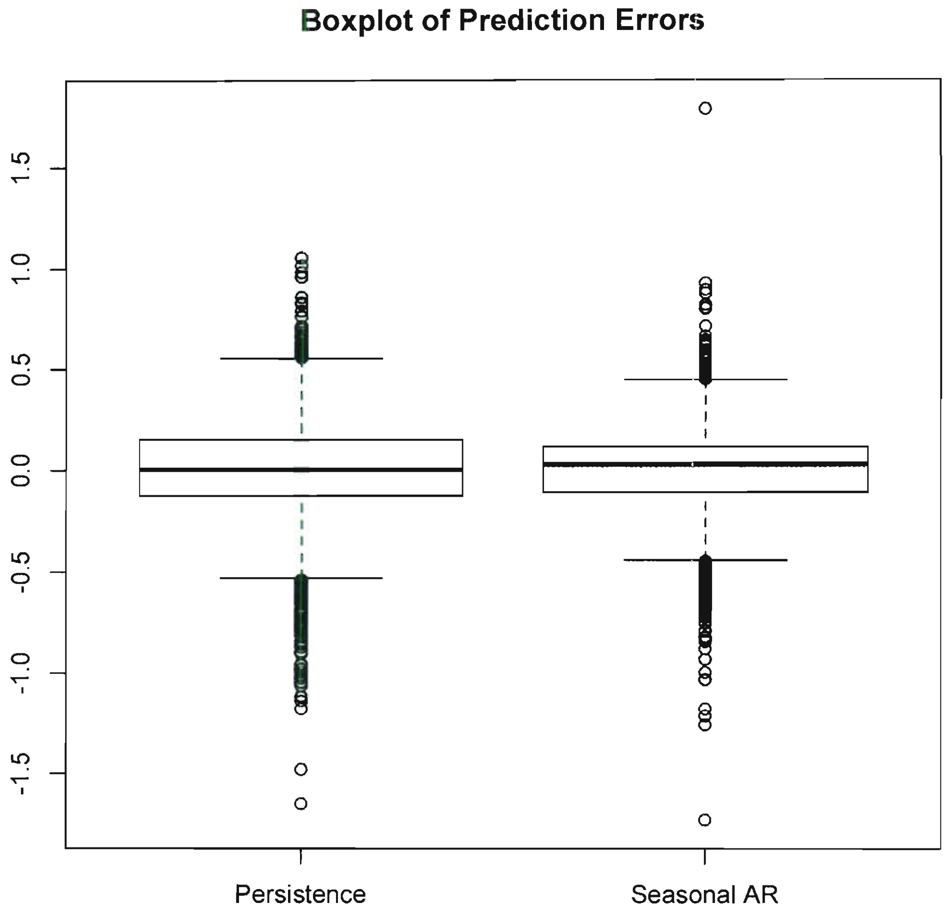


Figure 2.9 : Boxplots of the prediction errors for the Persistence (MSPE = $0.0713$) and Seasonal AR model (MSPE = $0.0498$).

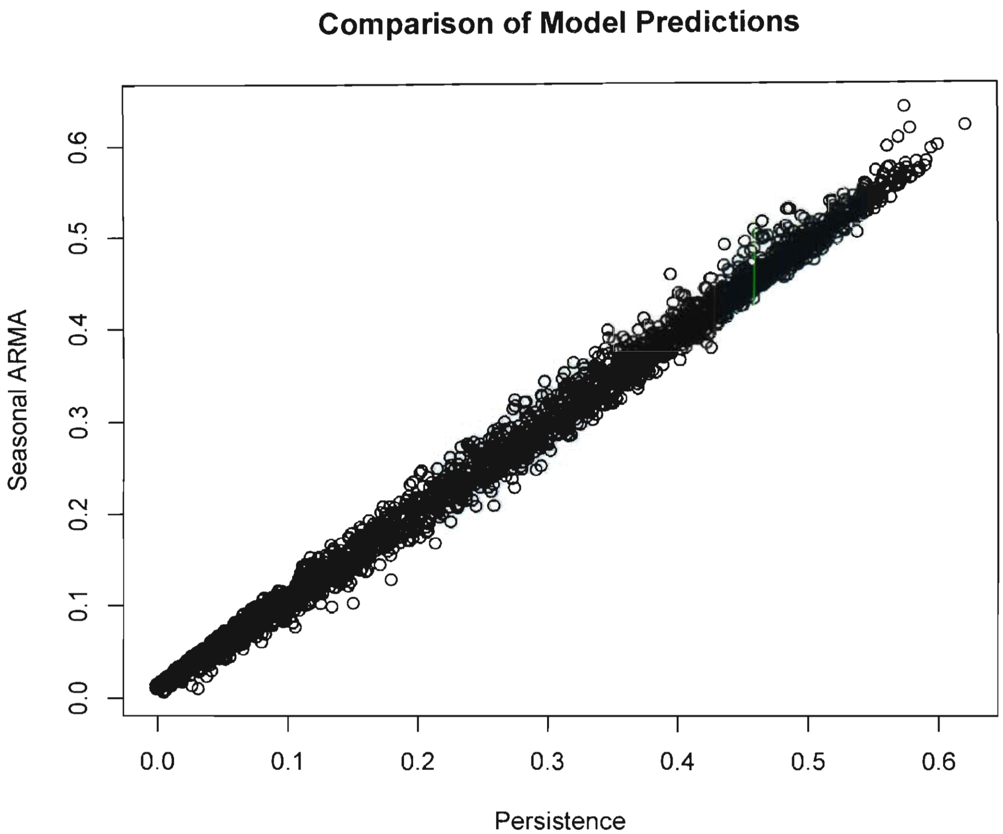


Figure 2.10 : Comparison of predicted values using the Persistence model and the Seasonal ARMA model.

to have not only a good forecast of how wind will generate during the day, but also an assessment of the level of uncertainty in that forecast," Saathoff said. "Since we don't have much control over wind, the key for grid reliability is to have a good wind forecast, and be prepared for the variability of wind as we are for load, rather than as a controllable capacity resource," Saathoff said (ERCOT, 2010).

# Chapter 3

# Power Prices

## 3.1 Background

Wind producers have two options of what to do with their supply of generated power. They can sign a bilateral contract where the producer agrees to sell a set amount of power to another party for a fixed price. The other option is to offer the power into a pool to be dispatched (Pinson *et al.* , 2007b). Participating in the market requires a forecast of future wind speeds or wind generation. The main characteristic of market participation is that the generator must place bids in advance, and are then charged for the difference between the bid and the actual production (Pinson *et al.* , 2007b). In ERCOT, there is currently no day-ahead pool so all power is contracted through bilateral agreements. In December 2010, ERCOT will switch from a zonal system to a nodal system and implement a day-ahead pool for electricity. Currently, wind producers do not participate in balancing energy services, but once nodal, ERCOT may allow wind producers to be part of the balancing energy services (Denny & O'Malley, 2007; Ummels *et al.* , 2007; Fabbri *et al.* , 2005).

A remarkable characteristic of energy commodity prices is the presence of price spikes. Such a phenomenon is usually explained by either supply sided (unplanned outages, wind plant ramp events) or demand-sided shocks (heat waves). We are trying to predict prices, and we see that the series exhibits spiky behavior. We want this to be apparent in our prediction of price as well, so we must determine what causes spikes, as well as how often they happen.

In general, electricity price series are known to exhibit seasonality, mean-reversion, high volatilities, and price spikes. The mean reversion can be explained by the fact that fundamental price equilibrium is set by the long run marginal costs of generation. However, strict mean reversion models cannot take into account the fat tails in the distribution of prices.

Electricity prices exhibit a few well known characteristics.

A) Mean Reversion - Power prices tend to fluctuate around values determined by the cost of production and the level of demand.

B) Seasonality - Power prices change by time of day, week, month and year in response to cyclical fluctuations in demand.

C) Non-storability - electricity cannot be stored and once generated it needs to be consumed almost immediately. The lack of storage means that electricity prices do not follow a 'smooth process' as prices of other commodities do.

D) Price Spikes - Power prices exhibit occasional price spikes due to supply shocks such as transmission constraints and unexpected outages.

E) Regional Differences - Due to the fact that electricity is not storable and transmission constraints, spot prices and forward curves may vary drastically from region to region.

We must have a method for defining when a price spike occurs. One such was is to define a threshold beyond which we consider the price a jump. We then use this threshold to filter out jump events. One common methods of choosing a threshold is that any price change larger than three standard deviations should be considered jump events.

As previously mentioned, a remarkable characteristic of electricity spot prices is the presence of price spikes. In a continuous-time framework, jump-diffusion models consider the possibility of large short-lived variations of the underlying variable and thus might be appropriate for modeling electricity spot-prices. Jump-diffusion models link price changes to the arrival of information, and consider the existence of two types of news: normal news, which produces continuous price dynamics and abnormal news, which causes discrete price jumps and whose arrival is modeled using a probabilistic discrete time process.

Blanco and Soronow investigate using a jump diffusion model to explain power prices. They find the following, "The main limitations of the original Merton 1976 jump diffusion model when applied to power markets is that it assumes the continuous lognormal diffusion process and the Poisson controlled process are independent of one another. This is not the case in electricity. For example, prices are highly unlikely to spike overnight when demand is very low. The nature of price jumps in electricity markets requires a generalization of Merton's model" (Blanco & Soronow, 2001).

Jump-diffusion processes have three model parameters that allow us to model outage events. In order to model jumps, we need to determine their probability of occurance, or "jump frequency", their expected size, and their expected variability or standard deviation. Once you determine the threshold, you can then determine the jump frequency by counting the observations above the threshold.

There are several problems one must consider when attempting to forecast time electricity price time series with jumps. First, the size, volatilities and frequency of jumps in electricity prices are not constant and perhaps need to vary over time. Also, the speed at which prices revert from jumps to long run means depend on the type of event that caused the jump in the first place. When electricity prices spike extremely high due to an event, they tend to return to mean levels quickly, whereas if load is high and causes prices to rise, they tend to return to previous levels much more slowly. Jump events may not be independent. Many simple models assume that jumps are not serially correlated. In this case, a regime-switching model may be a better fit.

A regime-switching model is used by Schindlmayr to predict spot price data from the European Energy Exchange (Schindlmayr, 2005). The author uses two regimes, one to represent a normal regime, and another for a spike regime, where the spikes are characterized by strong mean-reversion and high volatility. The normal state is a seasonal function of $sine$ and $cosine$ of time. When the model predicts a spike, a historical spike level is drawn randomly according to several requirements including on peak or off peak, and time of year.

Another way to model a process with spikes is a Poisson process. Take a sequence $\{\tau_i, i \geq 1\}$ of independent exponential random variables with parameter $\lambda$, that is, with cumulative distribution function $P[\tau_i \geq y] = e^{-\lambda y}$ and let $T_n = \sum_{i=1}^{n} \tau_i$. The process

$$N_t = \sum_{n \geq 1} 1_{t \geq T_n} \tag{3.1}$$

is called the Poisson process with parameter $\lambda$, where $1_{t \geq T_n}$ is an indicator function that is equal to 1 when $t \geq T_n$ and 0 otherwise. For example, if the waiting times between buses at a bus stop are exponentially distributed, the total number of buses arrived up to time t is a Poisson process. The paths of a Poisson process are piecewise constant (right-continuous with left limits or RCLL), with jumps of size 1 only. The jumps occur at times $T_i$ and the intervals between jumps (the waiting times) are exponentially distributed. At every time $t > 0$, $N_t$ has the Poisson distribution with parameter $\lambda t$, that is, it is integer-valued and

$$P[N_t = n] = e^{-\lambda t} \frac{(\lambda t)^n}{n!}. \tag{3.2}$$

## 3.2 Data Description

In the ERCOT electricity market, the price paid to generators who participate in the ancillary services market is called the market clearing price of energy (MCPE) (Electric Reliability Council of Texas, 2010). There is a balancing price for each zone of the grid every 15 minutes. Balancing energy prices are published and publicly available on ERCOT's website (http://www.ercot.com/mktinfo/). The price data series that we analyze consists of the MCPE for the West zone for the entire 2008 year. The prices are in U.S. dollars per

MWh. One year of 15 minute data is a series of length 35136. Figure 3.1 is a plot of the time series of West zone prices in 2008.

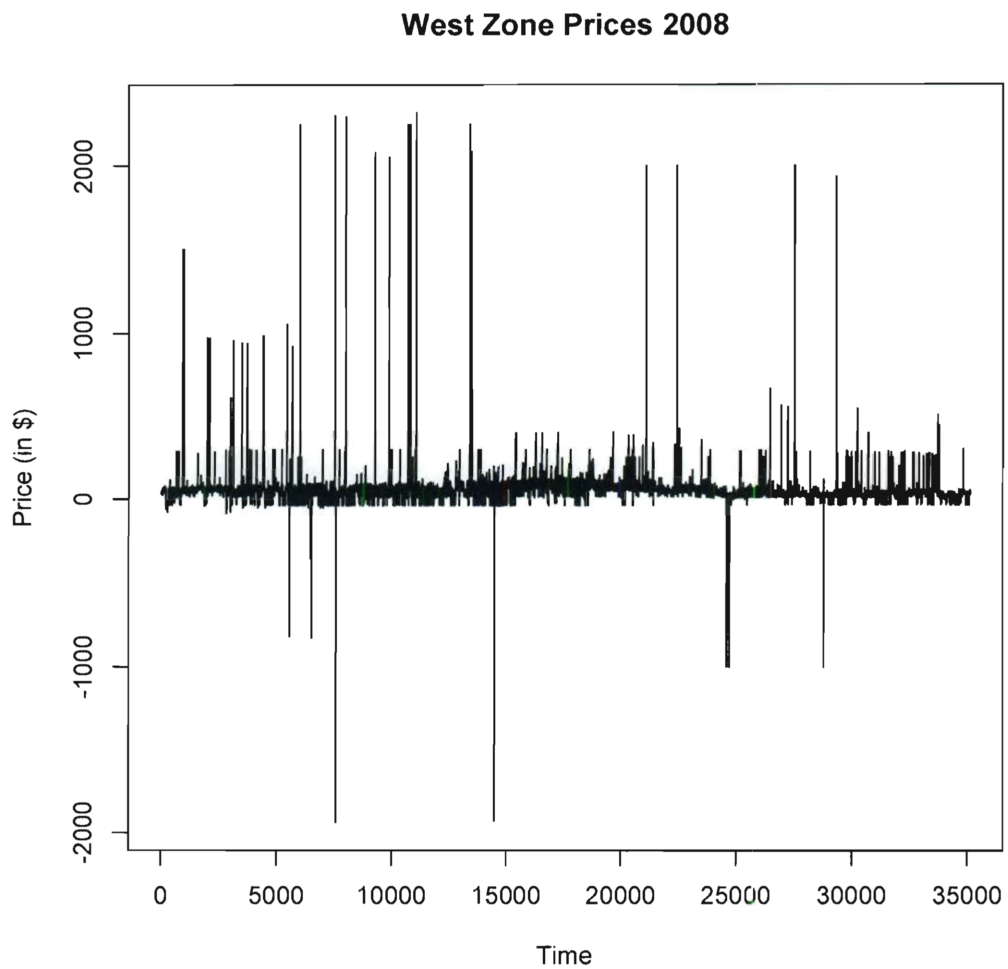


Figure 3.1 : 2008 West Zone MCPE

Another piece of data that we use in the prediction of the price time series is hourly data on wind power generation, published real-time on the ERCOT website, and made available for research purposes. Until 2009, the wind generation was only recorded as an aggregate system wind generation, but wind generation is now recorded for each generator.

We also use data on the load or demand on the grid, as well as data on the load for the West zone. The load is constantly monitored by ERCOT so that supply constantly equals demand. The real-time load is publicly available on the ERCOT website, and there are hourly load data archives also publicly available at http://www.ercot.com/gridinfo/load/.

We also incorporate information on unplanned outages in the grid. An unplanned outage is when a generator has to decrease generation due to unforeseen circumstances. All power plants have outages for maintenance, but these must be registered and approved by ERCOT in advance. An unplanned outage may be caused by many different things including mechanical failures, equipment malfunction, and personnel accidents (Milligan, 2001). Generation outage data is compiled by ERCOT and includes both planned and unplanned outages and is available for research purposes only. We focus on the unplanned outages for our analysis because a planned outage is known in advance to ERCOT and the generation will come from another source.

Finally, we use system imbalance data. A imbalance is the difference between the scheduled energy and the real-time demand of energy. This imbalance must be made up for in the balancing energy services market. ERCOT publishes imbalance data for each 15 minute period of the day (96 periods in one day) with the balancing price data and is publicly available at http://www.ercot.com/mktinfo/prices/mcpe.

## 3.3 Model

### 3.3.1 Overview of Modeling Strategy

The price time series shown in Figure 3.1 has three distinct features at first glance. First, we have a series that represents the "typical" behavior of prices. Second, we see that we have price spikes of up to $2250 (an ERCOT imposed maximum). These do not happen often, and appear to be outliers in the histogram of prices, as shown in Figure 3.2. Finally, we have negative price spikes. The largest negative price spike is -$1938.49.

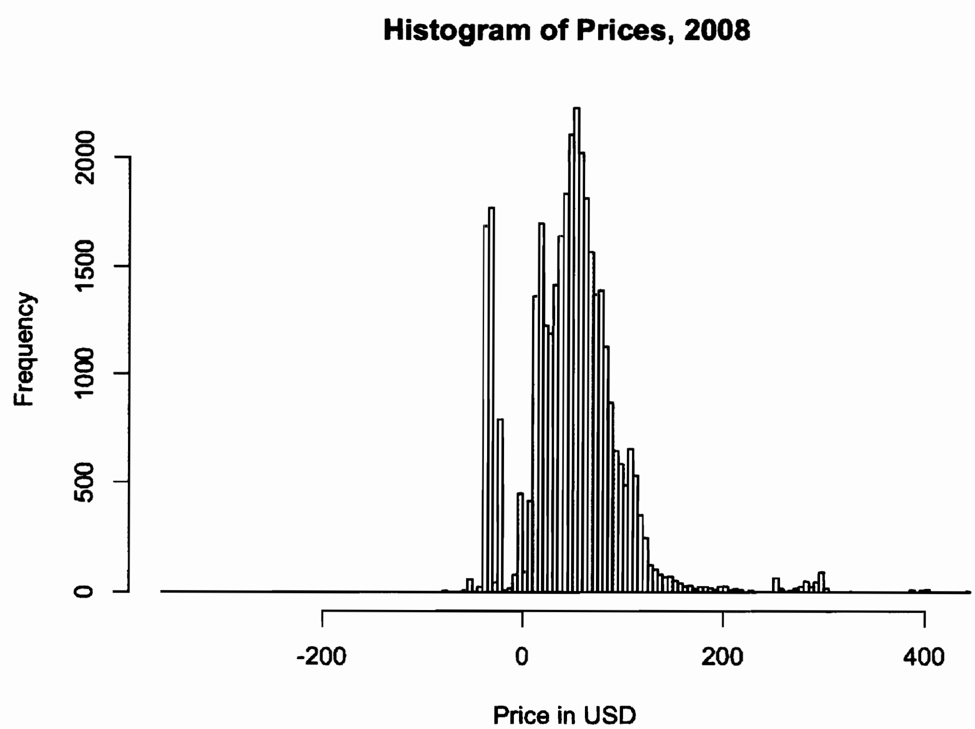


Figure 3.2 : Histogram of West zone prices for 2008, with 157 outliers removed.

We choose to split our time series up into distinct parts in order to model each separately and then put the pieces back together to do a final prediction. We model the positive and negative price spikes separately as we hypothesize that the positive and negative spikes are caused by different mechanisms.

### "Typical" Behavior Model

In order to model the typical price behavior, we impose two thresholds on the price series, $\tau_1$ and $\tau_2$, where $\tau_1$ is the threshold between negative price spikes and typical behavior and $\tau_2$ is the threshold between typical behavior and positive price spikes.

In order to determine the model for our typical price behavior, we examine how the prices behave on a daily basis. Figure 3.3 shows the prices for two consecutive days randomly drawn from the year. We note a daily seasonal pattern, where the prices early in the first day are similar in level to the prices early in the second day. This also holds true for mid-day and later in the day. This observation leads us to believe that we must incorporate this seasonality information into the model.

We follow the ideas of (Contreras *et al.* , 2003) and model this as an autoregressive moving (ARMA) average model to capture autocorrelation in the data, and in addition we include a seasonal term to capture the daily trend.

The seasonal ARMA model is denoted $ARMA(p, q) \times (P, Q)_h$ where $p$ is the number of AR terms, $q$ is the number of MA terms, $P$ is the number of seasonal AR terms, $Q$ is the number of seasonal MA terms, and $h$ is the period of the seasonality.

Let $X_t$ denote our "typical" price series (between thresholds $\tau_1$ and $\tau_2$). Then,

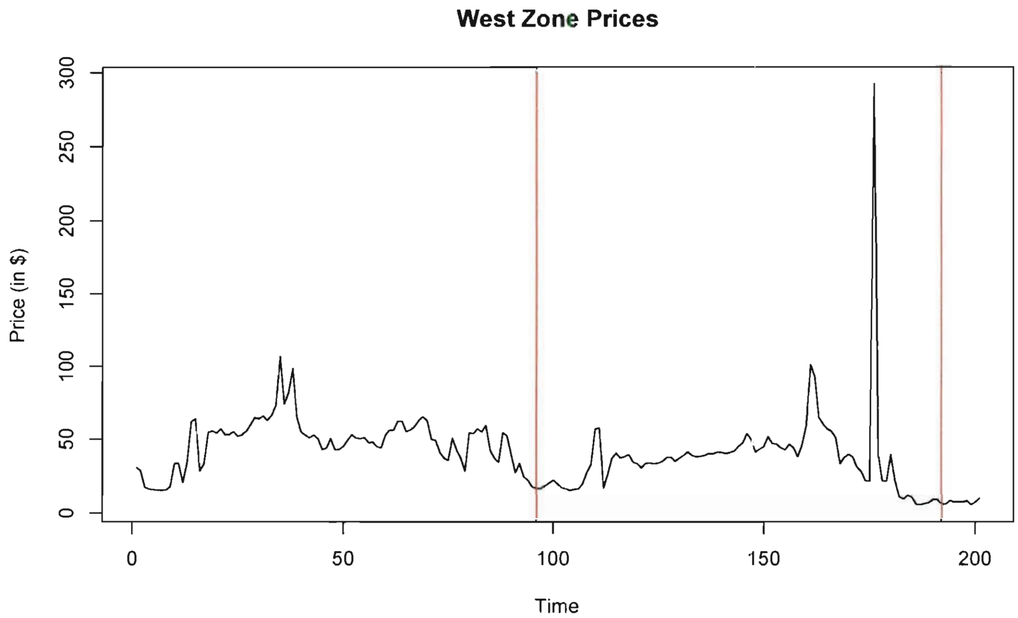


Figure 3.3 : Daily Seasonal Pattern

$$\Phi(B^h)\phi(B)(X_t - \mu) = \Theta(B^h)\theta(B)\epsilon_t, \tag{3.3}$$

where $\epsilon_t$ is assumed to be an independent and identically distributed random variable where $\epsilon_t \sim N(0, \sigma^2)$, and $B$ is the backshift operator. By definition, the backshift operator functions according to $B^i W_t = W_{t-i}$. Let us also define,

$$\Phi(B^h) = 1 - \Phi_1 B^h - \Phi_2 B^{2h} - \ldots - \Phi_P B^{Ph} \tag{3.4}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_P B^p \tag{3.5}$$

$$\Theta(B^h) = 1 - \Theta_1 B^h - \Theta_2 B^{2h} - \ldots - \Theta_Q B^{Qh} \tag{3.6}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q. \tag{3.7}$$

**Positive Spikes**

All price spikes are caused by an imbalance between supply and demand. We investigate exactly what causes these imbalances while predicting the spikes. When modeling the price spikes, we must model not only when the spikes occur, but also the magnitude of the spikes.

We model the occurrence of price spikes using a transformation of the spikes into times between spikes, or durations. The Autoregressive Conditional Duration (ACD) model comes from a group of models known as duration models. Duration models are concerned with time intervals between events. In our case, we consider durations the time between price spikes, where a spike is defined as anything above three standard deviations above the mean price. Longer durations mean that there are no significant upsets in the supply demand balance, whereas, shorter durations mean that there is a period of instability in the supply demand equilibrium of the ERCOT power market.

The ACD model was first introduced in 1998 by Engle and Russell in a paper titled "Autoregressive Conditional Duration: A new model for irregularly spaced data". They use the model to describe the time between trades for stocks. We first layout the background of the model, and then specify our use of the model (**?**).

Define the duration as $d_i = \Delta t_i$. Then let $\psi_i = \mathbb{E}(x_i|F_{i-1})$ be the conditional expectation of the duration between the $(i-1)$th and $i$th events, where $F_{i-1}$ is the information set available at the $(i-1)$th event. So, $\psi_i$ is just the expected duration given the previous information.

In its most basic formulation, the ACD(p,q) model is defined as:

$$d_i = \psi_i \epsilon_i \tag{3.8}$$

where $\{\epsilon\}$ is a sequence of $iid$ non-negative random variables such that $\mathbb{E}(\epsilon_i) = 1$. In the seminal paper by Engle and Russell, $\epsilon_i$ follows a standard exponential or standardized Weibull distribution and $\psi_i$ is in the following form:

$$\psi_i = \alpha_0 + \sum_{j=1}^{p} \alpha_j d_{i-j} + \sum_{j=1}^{q} \beta_j \psi_{i-j}. \tag{3.9}$$

Noticing the similarities to the GARCH models, the process $\eta_i = d_i - \psi_i$ is a martingale difference sequence, and the ACD(p,q) model can be rewritten in the following form: (Tsay, 2005)

$$x_i = \alpha_0 + \sum_{j=1}^{max(p,q)} (\alpha_j + \beta_j) x_{i-j} + \sum_{j=1}^{q} \beta_j \eta_{i-j} + \eta_j. \tag{3.10}$$

Looking at the histogram of durations in Figure 3.4, we note that there are many smaller durations, but that we also see durations of up to length 3,942, or just over 41 days.

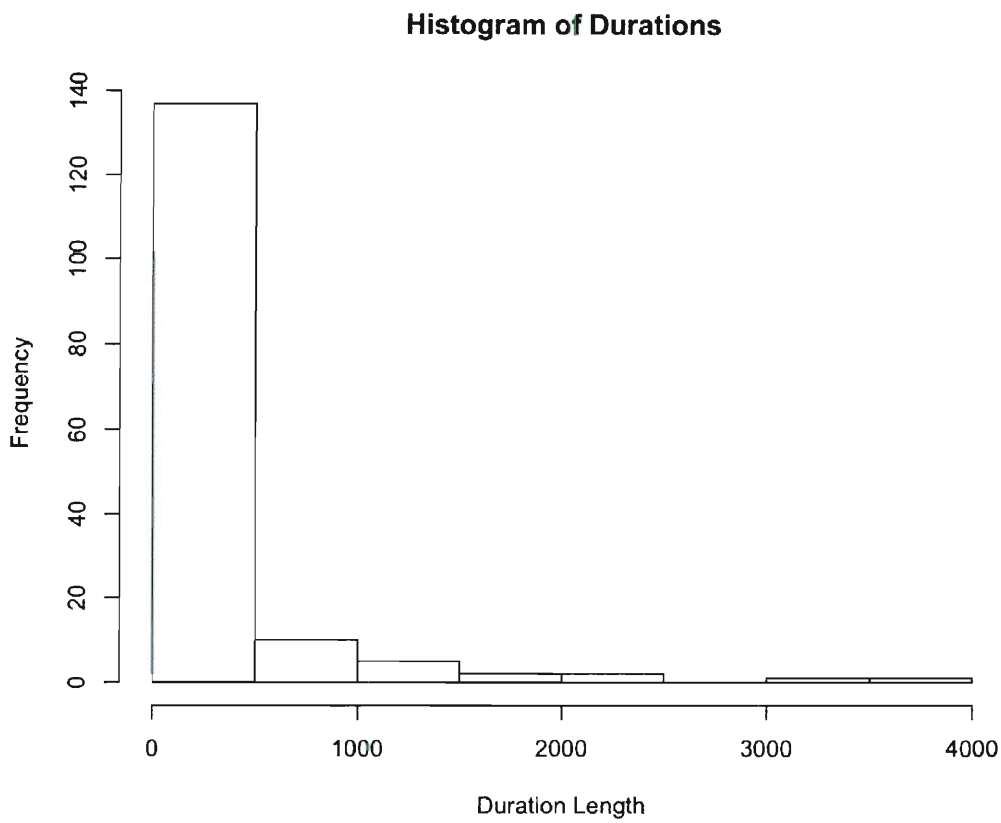


Figure 3.4 : Histogram of Durations

Due to the large difference between a duration of 0 and a duration of 3,942, we choose to employ a threshold ACD model (TACD). We threshold the durations into two groups, one of short durations, and one of long durations. Short durations mean price spikes tend to happen close to one another, and long durations mean that price spikes happen further apart from one another.

We denote the simple two-regime threshold autoregressive conditional duration model as $TACD(2; p, q)$, and define it as below.

$$\Delta t \equiv d_i = \begin{cases} \psi_i \epsilon_{1i} & \text{if } d_{t-l} \leq \omega, \\ \psi_i \epsilon_{2i} & \text{if } d_{t-1} > \omega. \end{cases} \tag{3.11}$$

Where $l$ is a positive integer, $d_{t-l}$ is the threshold variable, $\omega$ is the threshold and $\psi_i$ is defined as

$$\psi_i = \begin{cases} \alpha_{10} + \sum_{j=1}^{p} \alpha_{1j} d_{i-j} + \sum_{k=1}^{q} \beta_{1k} \psi_{i-k} & \text{if } d_{t-l} \leq \omega, \\ \alpha_{20} + \sum_{j=1}^{p} \alpha_{2j} d_{i-j} + \sum_{k=1}^{q} \beta_{2k} \psi_{i-k} & \text{if } d_{t-l} > \omega. \end{cases} \tag{3.12}$$

Once we have modeled the times the spikes will occur, we have to then model the magnitude of the spikes. Since we believe that spikes are caused by an imbalance in supply and demand, we hypothesize that the variables that drive the magnitude of spikes would be load (or demand), unexpected outages (plants that must stop generation due to unforeseen circumstances), previous prices, wind power generation, and imbalance on grid. We use a simple linear regression model to model the magnitude of the spikes. The model for the positive spikes can be written as

$$Y^+ = Z_+ \beta_+ + \epsilon_+ \tag{3.13}$$

respectively. In the model, $Z_+$ is a matrix of covariates, and $\beta_+$ is a vector of the regression coefficients of the covariates. We assume that $\epsilon_+$ is independent and identically distributed with a Normal distribution of mean 0 and variance $\sigma_+^2$.

### Negative Spikes

We model the negative spikes in an identical fashion to the positive spikes. The only difference is that we do not have as many data points for negative spikes (they occur less frequently), so we choose to model the occurrence of negative price spikes as an $ACD(p,q)$ model rather than a $TACD(2;p,q)$ using Equation 3.8.

Similarly, we then model the magnitude of the spikes using a multiple linear regression, shown below.

$$Y^- = Z_-\beta_- + \epsilon_- \tag{3.14}$$

where $Z_-$ is a matrix of covariates, and $\beta_-$ is a vector of the regression coefficients of the covariates. We assume that $\epsilon_-$ is independent and identically distributed with a Normal distribution of mean 0 and variance $\sigma_-^2$.

### 3.3.2 Model Definition

Let us denote the MCPE for the West zone at time $t$ as $P_t$. We model the price series as the linear combination of a 'typical' price process, and two spike series. Let us define our model as the following

$$P_t = X_t + \delta^+(\Delta_+ t)Y_t^+ + \delta^-(\Delta_- t)Y_t^- \tag{3.15}$$

where,

$$X_t = \text{"typical" price process} \tag{3.16}$$

$$Y_t^+ = \text{positive spike process} \tag{3.17}$$

$$Y_t^- = \text{negative spike process} \tag{3.18}$$

and,

$$\delta^+(\Delta_+ t) = \begin{cases} 1 & \text{if } t \text{ is a spike time for the positive spike series,} \\ 0 & \text{otherwise} \end{cases},$$

$$\delta^-(\Delta_- t) = \begin{cases} 1 & \text{if } t \text{ is a spike time for the negative spike series,} \\ 0 & \text{otherwise} \end{cases}.$$

Notice that the coefficients for the spike series are a function of $\Delta_j t$ where $j = +, -$. Define the following,

$$\Delta_+ t \equiv d_i^+ = t_i^+ - t_{i-1}^+$$

$$\Delta_- t \equiv d_i^- = t_i^- - t_{i-1}^-$$

where $t_i^+$ is the $i$th spike time for the positive spikes ( $i = 1, \ldots, N_+$ ), and $t_i^-$ is the $i$th spike time for the negative spikes ( $i = 1, \ldots, N_-$ ).

Recall that the first term, $X_t$, the "typical" price series is modeled using a multiplicative seasonal ARMA model and can be written as

$$\Phi(B^h)\phi(B)(X_t - \mu) = \Theta(B^h)\theta(B)\epsilon_t, \tag{3.19}$$

where,

$$\begin{aligned} \Phi(B^h) &= 1 - \Phi_1 B^h - \Phi_2 B^{2h} - \ldots - \Phi_P B^{Ph} && (3.20) \\ \phi(B) &= 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_P B^p && (3.21) \\ \Theta(B^h) &= 1 - \Theta_1 B^h - \Theta_2 B^{2h} - \ldots - \Theta_Q B^{Qh} && (3.22) \\ \theta(B) &= 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q. && (3.23) \end{aligned}$$

The magnitudes of the spike series are modeled using a simple linear regression for each spike process which are written as,

$$\begin{aligned} Y_t^+ &= Z_+\beta_+ + \epsilon_+, && (3.24) \\ Y_t^- &= Z_-\beta_- + \epsilon_-. && (3.25) \end{aligned}$$

$Z_+$ and $Z_-$ contain lagged covariates wind generation, system load, unplanned outages, system imbalance, and the lagged price series.

And finally, the indicator functions, $\delta^+$ and $\delta^-$, that determine if we have a price spike are functions of $\Delta_+ t$ and $\Delta_- t$, respectively. The $\Delta_j t$ where $j = +, -$, are modeled using ACD models as defined below.

$$d_i^+ = \psi_{+i}\zeta_{+i} \tag{3.26}$$

$$d_i^- = \psi_{-i}\zeta_{-i}, \tag{3.27}$$

where,

$$\psi_{+i} = \begin{cases} \alpha_{10} + \sum_{j=1}^{p} \alpha_{1j} d_{1i-j}^+ + \sum_{j=1}^{q} \beta_{1j}\psi_{1i-j} & \text{if } d_{i-l}^+ \leq \omega \\ \alpha_{20} + \sum_{j=1}^{p} \alpha_{2j} d_{2i-j}^+ + \sum_{j=1}^{q} \beta_{2j}\psi_{2i-j} & \text{if } d_{i-l}^+ > \omega \end{cases} \tag{3.28}$$

$$\psi_{-i} = \alpha_0^- + \sum_{j=1}^{p} \alpha_j^- d_{i-j}^- + \sum_{j=1}^{q} \beta_j \psi_{i-j}^-. \tag{3.29}$$

and $\zeta_{+i}$ and $\zeta_{-i} \sim Exp(1)$. $\psi_{+i}$ and $\psi_{-i}$ are the parameters of 2 different Poisson processes.

### 3.3.3 Model Fitting and Parameter Estimation

#### Threshold Parameters

In our model for $P_t$, we have three threshold parameters that we must estimate. The first is the threshold $\tau_1$, the price at which we define the negative price spikes as all $P_t < \tau_1$. The second threshold is $\tau_2$, the price at which we define the positive price spikes as all $P_t > \tau_2$. The third threshold is $\omega$. We define $\omega$ as the duration length where all $d_i < \omega$ are labeled as short durations, and all $d_i > \omega$ are labeled as long durations.

We begin by estimating $\tau_1$. Wind farms receive a government subsidy of \$20 for generating electricity as well as tax breaks and accelerated depreciation of assets. The wind farms can still make money when the price is negative. The consensus is that wind farms can run at a negative price of up to -\$50 (). Using this consensus, we set $\tau_1$ at -\$50 to distinguish between negative prices, and negative price spikes. So with $\tau_1 = -\$50$, we have 16 negative price spikes.

Next we estimate $\tau_2$. Prices can be high when we have a high demand day, due to the generation stack. This just means that prices are based on the marginal fuel source, and on a high demand day, we use more expensive fuel to generate power so our prices are higher. Following the suggestion of (Lu & Pang, 2008) and (Zhang *et al.* , 2001), we pick a threshold of the mean of the price series, $\mu$ plus three times the standard deviation of the price series. $\tau_2$ distinguishes high prices from price spikes. With $\tau_2 = \$382.82$, we have 158 positive price spikes.

Finally we estimate $\omega$, the duration at which all smaller durations are labeled short durations and all larger durations are labeled long durations.

Looking at the predictions of the ACD model, we see two different types of regimes in the durations. One is a very short duration between events, and the other is a much longer duration between events. The ACD model is smoothing over the two, and giving us a

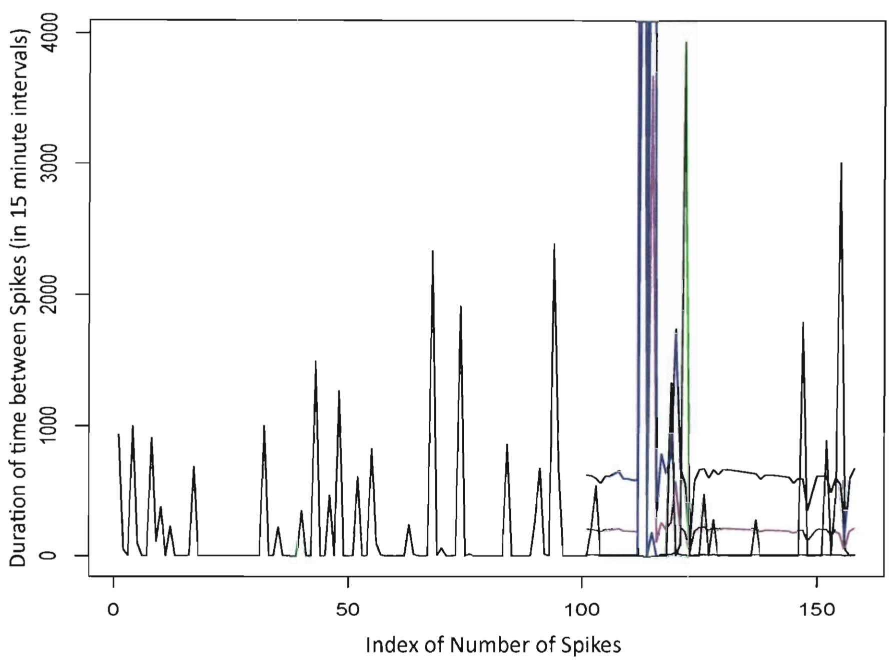


Figure 3.5 : Predicted Durations using ACD(1,1) model, the magenta curve is the prediction, and the blue curves are the 5% and 95% prediction intervals.

prediction that is almost never right. In order to solve this problem, we introduce a threshold ACD model, where the threshold variable is $x_{t-1}$. Once we estimate the threshold, we fit one ACD model above the threshold and one ACD model below the threshold.

In order to estimate the threshold, we begin by choosing a set of quantiles from .05 to .95, by .05, and fitting one ACD model to the data above the .05 quantile, and another ACD model to the data above the .05 quantile of the spike data. To choose the correct threshold for predictions we look at which set of ACD models minimize the negative log-likelihood. In our case, the .7 quantile was the quantile that minimized the negative log-likelihood,

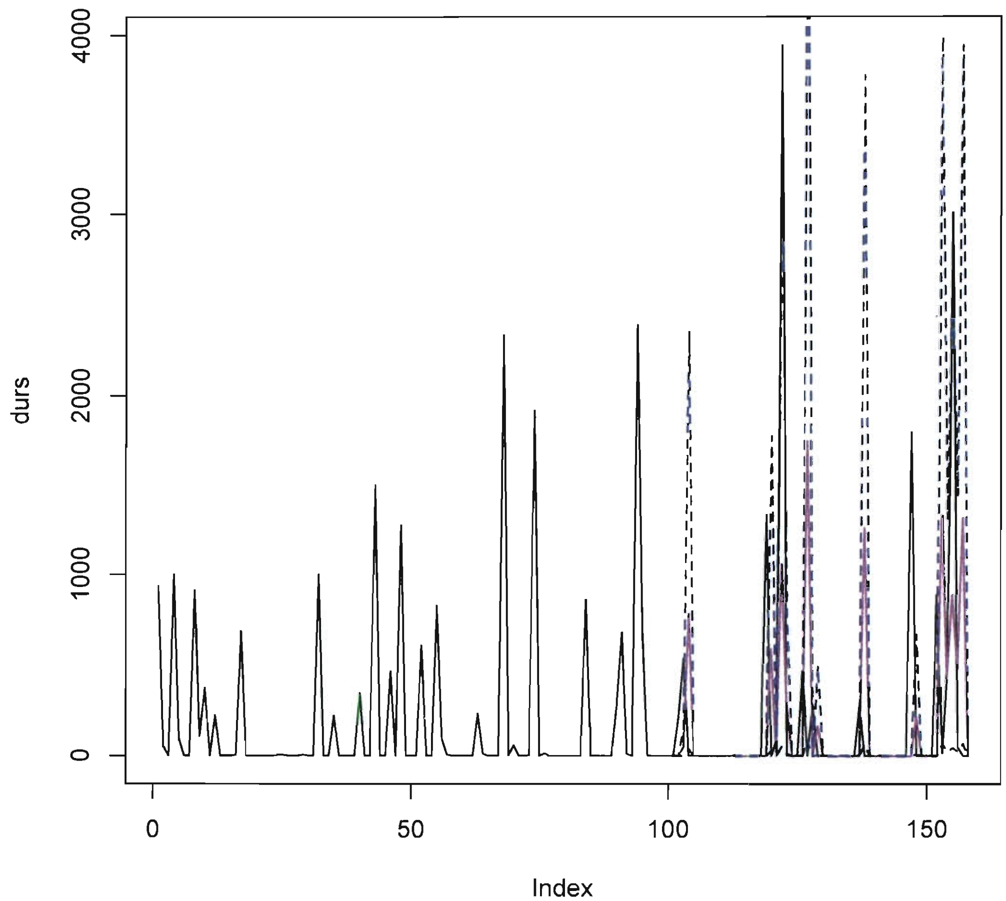


Figure 3.6 : Predicted Durations using Threshold ACD (TACD) model

so we pick this as our threshold. For the positive spike data, this was a duration of 8.5, meaning a time between spikes of 2 hours and 15 minutes.

### Estimation

In order to estimate the parameters of our models, we split our 2008 time series into a training and a test set. Our training set is the first 70% of our data, and our test set is the latter 30% of our data. This means we have 24,596 data points in our training set, and 10,540 in our test set. Figures 3.7 and 3.8 show the ACF and PACF of the thresholded training price series. Noticeably, the ACF has a seasonal pattern which shows up as a increase in autocorrelation at lags of multiples of 96. This is our daily seasonal pattern that we suspected existed in the data (there are 96 data points in a day). Note that we also see a spike in the PACF on the lags of multiples of 96.

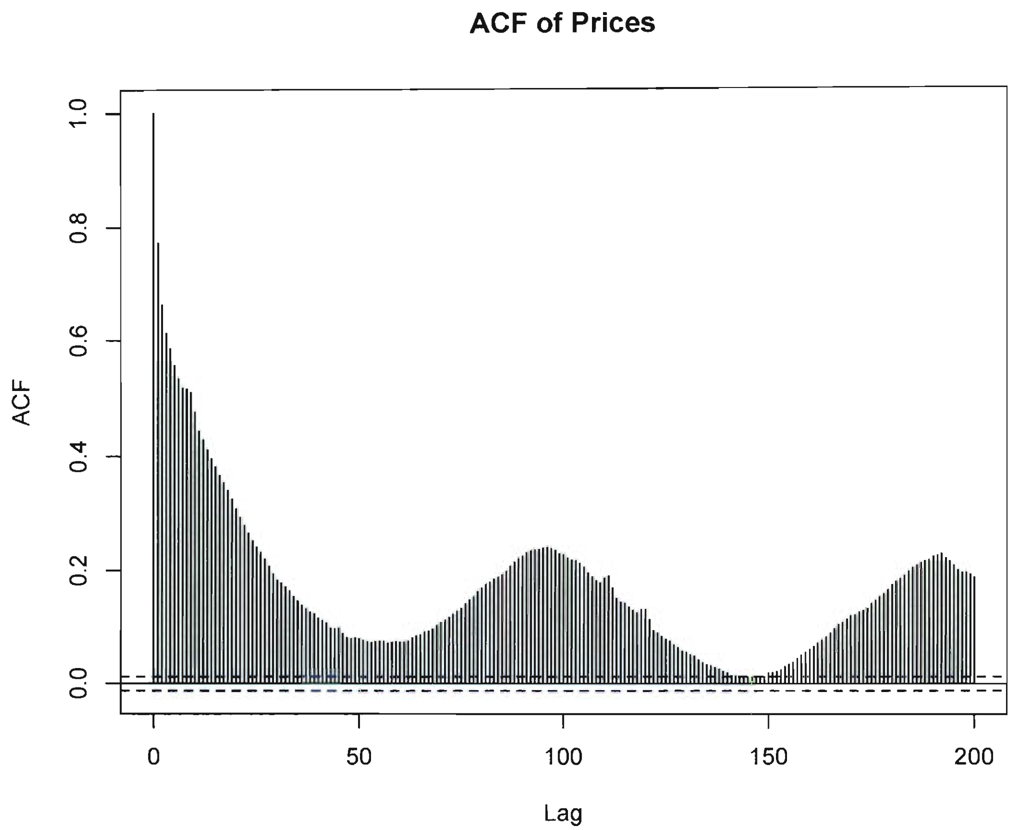


Figure 3.7 : ACF of thresholded training price series

By looking at the ACF, PACF, and the output from an automatic model choosing algo-

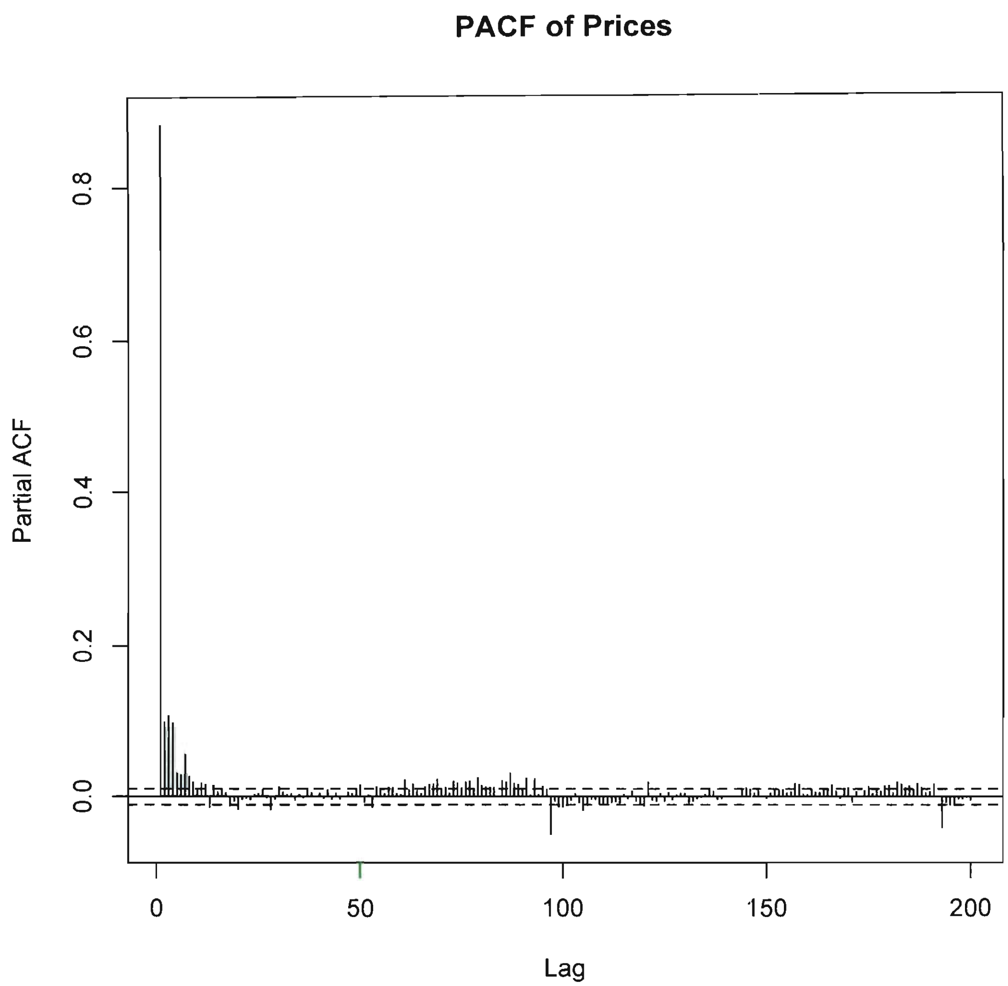


Figure 3.8 : PACF of thresholded training price series

rithm in R (auto.arima in the forecasting package), we choose to model the typical price series as an $ARMA(2,0) \times (1,0)_{96}$. This means we have two AR terms and one seasonal AR term. We do not include any moving average terms in the model. We can then write our model explicitly as

$$\Phi(B^{96})\phi(B)(X_t - \mu) = \epsilon_t, \tag{3.30}$$

where,

$$\Phi(B^{96}) = 1 - \Phi_1 B^{96} \tag{3.31}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2. \tag{3.32}$$

When we fit our model to the thresholded training set, and report the estimates in Table 3.1.

| | $\phi_1$ | $\phi_2$ | $\Phi_1$ | $\mu$ | $\sigma$ |
|---|---|---|---|---|---|
| Estimate | 0.8657 | 0.0410 | -0.0452 | 53.8399 | 22.95 |
| Standard Error | 0.0152 | 0.0138 | 0.0153 | 1.5699 | 0.6389 |

Table 3.1 : Estimated coefficients of $ARMA(2,0) \times (1,0)_{96}$ model.

Next we move to estimating our ACD models for the times between spikes. We start with the estimating the Threshold ACD model in Equation 3.11. We estimate a simple 2-regime threshold ACD(1,1) model. Following the suggestion of (Lu & Pang, 2008) we use the previous duration as our threshold variable. This means that we determine which model (low or high duration) based on the previous duration. We write the model explicitly as

$$\Delta t \equiv d_i^+ = \begin{cases} \psi_i \epsilon_{1i} & \text{if } d_{t-1} \leq 8.5, \\ \psi_i \epsilon_{2i} & \text{if } d_{t-1} > 8.5. \end{cases} \tag{3.33}$$

where $\phi_i$ is defined as,

$$\psi_i = \begin{cases} \alpha_{10} + \alpha_{11} d_{i-1} + \beta_{11} \psi_{i-1} & \text{if } d_{t-1} \leq 8.5, \\ \alpha_{20} + \alpha_{21} d_{i-1} + \beta_{21} \psi_{i-1} & \text{if } d_{t-1} > 8.5. \end{cases} \tag{3.34}$$

We fit this $TACD(2;1,1)$ model to the positive spike durations in our training data period, and report the coefficients in Table 3.2.

| | $\alpha_{j0}$ | $\alpha_{j1}$ | $\beta_{j1}$ |
|---|---|---|---|
| $j = 1$ | 1.6581 | 0.1519 | 0.6389 |
| Standard Error | 0.2416 | 0.0353 | 0.1961 |
| $j = 2$ | 0.0418 | 0.1238 | 1.0877 |
| Standard Error | 0.0317 | 0.0199 | 0.1760 |

Table 3.2 : Estimated coefficients of $TACD(2;1,1)$ model.

Now we estimate the times between the negative spikes. Due to the small amount of data, we only estimate a single $ACD(1,1)$ model for the times between negative spikes. The ACD model is written explicitly as

$$d_i^- = \phi_i^- \epsilon_i^- \tag{3.35}$$

where,

$$\phi_i^- = \alpha_0^- + \alpha_1^- d_{i-1}^- + \beta_1^- \phi_{i-1}^-. \tag{3.36}$$

We fit the $ACD(1, 1)$ model to the negative spike durations in our training data period, and report the coefficients in Table 3.3.

| | $\alpha_0^-$ | $\alpha_1^-$ | $\beta_1^-$ |
|---|---|---|---|
| Estimate | 1.0672 | 0.5470 | 0.1405 |
| Standard Error | 0.0219 | 0.1029 | 0.0569 |

Table 3.3 : Estimated coefficients of $ACD(1, 1)$ model.

Finally we move on to estimating the magnitude of the price spikes (both positive and negative), $Y_t^+$ and $Y_t^-$. We know that spikes are caused by an imbalance in the supply demand equilibrium. So, we create a multiple regression model using variables that will help predict the positive price spikes. Table 3.4 shows the regression of the predictors on the price spike for the training data. We ran a stepwise regression for the best AIC, and found that this model has the best fit. Our adjusted R-squared is 0.546, or we are able to expain 54.6% of the variation with this model. the p-value for the model is $1.09 \times 10^{-14}$ which means our model is significant.

Similar to the positive spikes, we model the magnitude of the negative spikes using a multiple regression. So, we create a multiple regression model using variables that will help predict the negative price spike. Table 3.3.3 shows the regression of the predictors on the negative price spikes for the training data. We ran a stepwise regression for the best AIC, and found that this model has the best fit. Our adjusted R-squared is 0.4796, or we are

| | Estimate | Std. Error |
|---|---|---|
| (Intercept) | 1559.6685 | 219.6943 |
| Price Lag1 | 0.0573 | 0.1694 |
| Price Lag2 | 0.1754 | 0.0758 |
| Load Lag1 | -0.0537 | 0.0166 |
| Load Lag2 | -0.0938 | 0.0339 |
| Imbalance Lag1 | 0.0001 | 0.0000 |

Table 3.4 : Estimated coefficients of model for $Y_t^+$.

able to expain 47.9% of the variation with this model. the p-value for the model is 0.0976 which means our model is significant at the 10% level.

| | Estimate | Std. Error |
|---|---|---|
| (Intercept) | -1047.9200 | 667.6109 |
| Price Lag1 | -0.2335 | 0.9255 |
| Price Lag2 | 6.2805 | 7.4460 |
| Windout Lag1 | -0.0888 | 0.4351 |
| Load Lag1 | -0.6230 | 1.0949 |
| Imbalance Lag1 | -0.4726 | 0.8454 |

Table 3.5 : Estimated coefficients of model for $Y_t^-$.

## 3.4 Results

Now that we have modeled the three parts of the price time series separately, and estimated all parameters in the model, we now add them together to make predictions of power prices in west Texas for the latter 30% of 2008. Figure 3.9 shows the year 2008 data in black. The horizontal green line is at \$382.80, our positive spike threshold, and the horizontal red line is at -\$50. The magenta series is the prediction. Figures 3.10 and 3.11 show the predictions

Parameter Estimates

| | | Estimate | Std. Error |
|---|---|---|---|
| Thresholds | $\tau_1$ | -\$50 | - |
| | $\tau_2$ | \$382.82 | - |
| | $\omega$ | 8.5 | - |
| Seasonal ARMA | $\phi_1$ | 0.8657 | 0.0152 |
| | $\phi_2$ | 0.0410 | 0.0138 |
| | $\Phi_1$ | -0.0452 | 0.0153 |
| | $\mu_1$ | 53.8399 | 1.5699 |
| | $\sigma$ | 22.95 | .6389 |
| TACD | $\alpha_{10}$ | 1.6581 | 0.2416 |
| | $\alpha_{11}$ | 0.1519 | 0.0353 |
| | $\beta_{11}$ | 0.6389 | 0.1961 |
| | $\alpha_{20}$ | 0.0418 | 0.0317 |
| | $\alpha_{21}$ | 0.1238 | 0.0199 |
| | $\beta_{21}$ | 1.0877 | 0.1760 |
| ACD | $\alpha_0$ | 1.0672 | 0.0319 |
| | $\alpha_1$ | 0.5470 | 0.1029 |
| | $\beta_1$ | 0.1405 | 0.0569 |

Parameter Estimates

| | | Estimate | Std. Error |
|---|---|---|---|
| $Y^+$ | (Intercept) | 1386.6152 | 188.9630 |
| | Price Lag1 | 0.3508 | 0.0820 |
| | Wind Gen Lag2 | -0.0712 | 0.02157 |
| | Load Lag2 | -0.05096 | 0.02520 |
| | Imbalance Lag1 | 0.62187 | 0.22996 |
| $Y^-$ | (Intercept) | -33.9200 | 4.204 |
| | Price Lag1 | 0.2204 | 0.0171 |
| | Price Lag2 | -0.0446 | 0.0180 |
| | Wind Gen Lag2 | 0.0015 | 0.0008 |
| | Load Lag1 | 0.007 | 0.0041 |
| | Load Lag2 | -0.0079 | 0.0041 |

Table 3.6 : Parameter estimates for price prediction model with corresponding standard errors.

for the spike series.

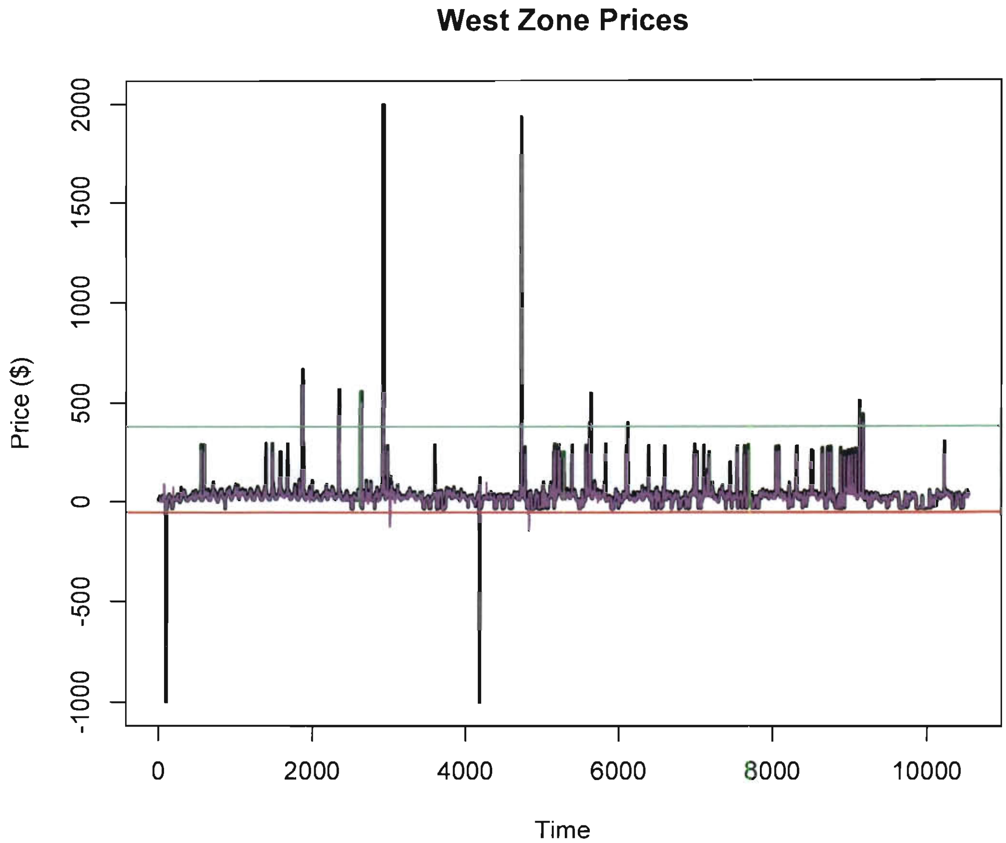


Figure 3.9 : Sept 13, 2008 to Dec 31, 2008 Price Predictions

The prediction appears to do well, but we need to compare our method of prediction in order to determine how much our prediction improves on another prediction method. A commonly used comparison prediction method for electricity prices is the persistence method. The persistence method uses the previous price as the forecast for the next price. This method performs surprisingly well with hourly, 15 minute, and 5 minute data(Lu & Pang, 2008). The model can be explicitly written as

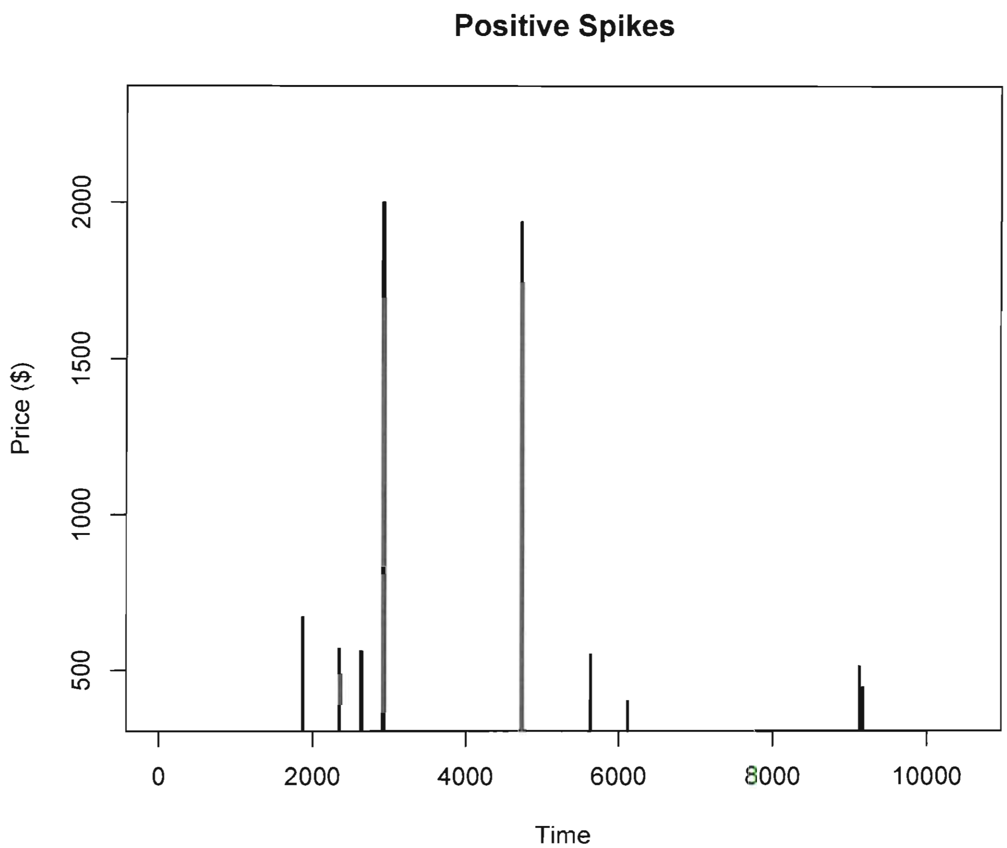


Figure 3.10 : Sept 13, 2008 to Dec 31, 2008 Positive Spike Price Predictions

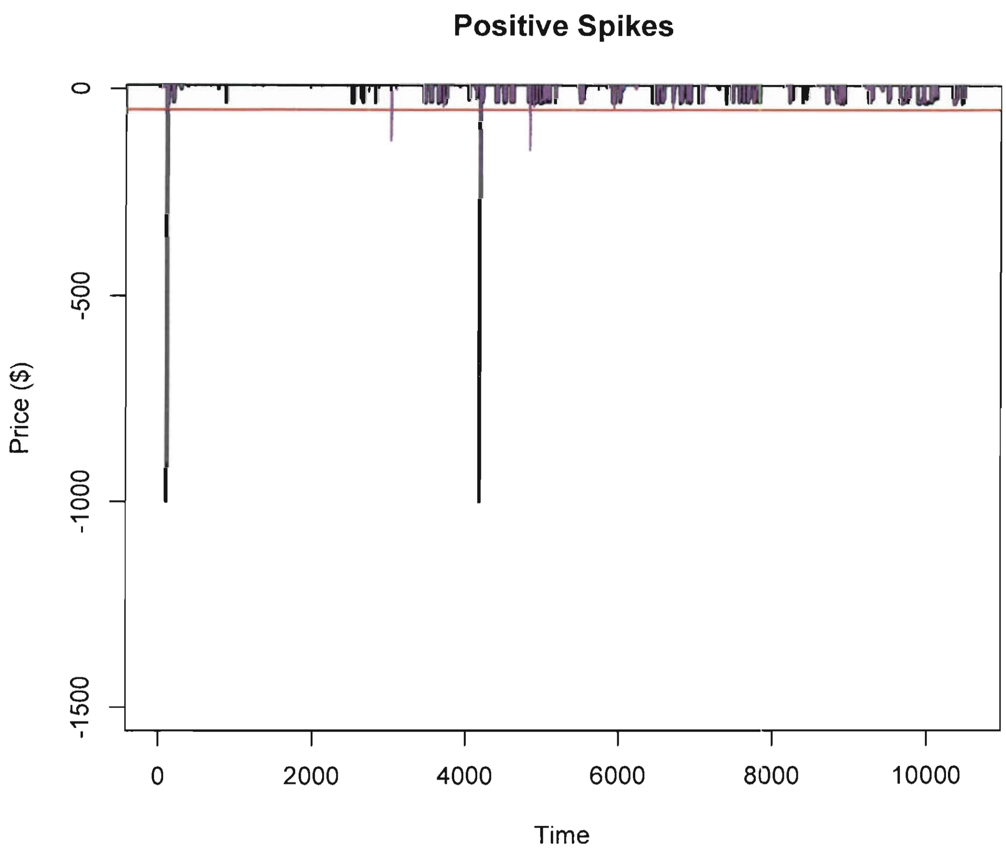


Figure 3.11 : Sept 13, 2008 to Dec 31, 2008 Negative Spike Price Predictions

$$P_t = P_{t-1} + \epsilon_t. \tag{3.37}$$

Our model as described in Section 3.3.2 has a mean squared prediction error of 35.7021. When we predict prices using the persistence model, we have a mean squared prediction error of 73.1337. Not only does our model have a lower RMSE than the persistence model, but we achieve a 48% improvement. Figure 3.12 shows boxplots of the prediction errors. A forecast method should be evaluated by the extent to which it can improve on existing forecasting methods.

### 3.4.1 Resampling

In addition to the forecasting of prices, we are also interested in the distribution of these forecasts. Because our model is a linear function of the typical behavior, the positive spikes, and the negative spikes, there is not an obvious method of determining prediction intervals. In order to evaluate the distribution of the predictions and the stability of our estimated parameters, we take a resampling approach.

We treat the year of data as a circle and randomly choose a point to start our new year. We then estimate all parts of the model using the first 70% of the data. We perform predictions using the estimated models, and keep track of the model parameter estimates as well as the predictions. This will be useful when we evaluate our economic model in Chapter 4 because we will be able to determine if our model estimates have an effect on the revenue for a wind farm.

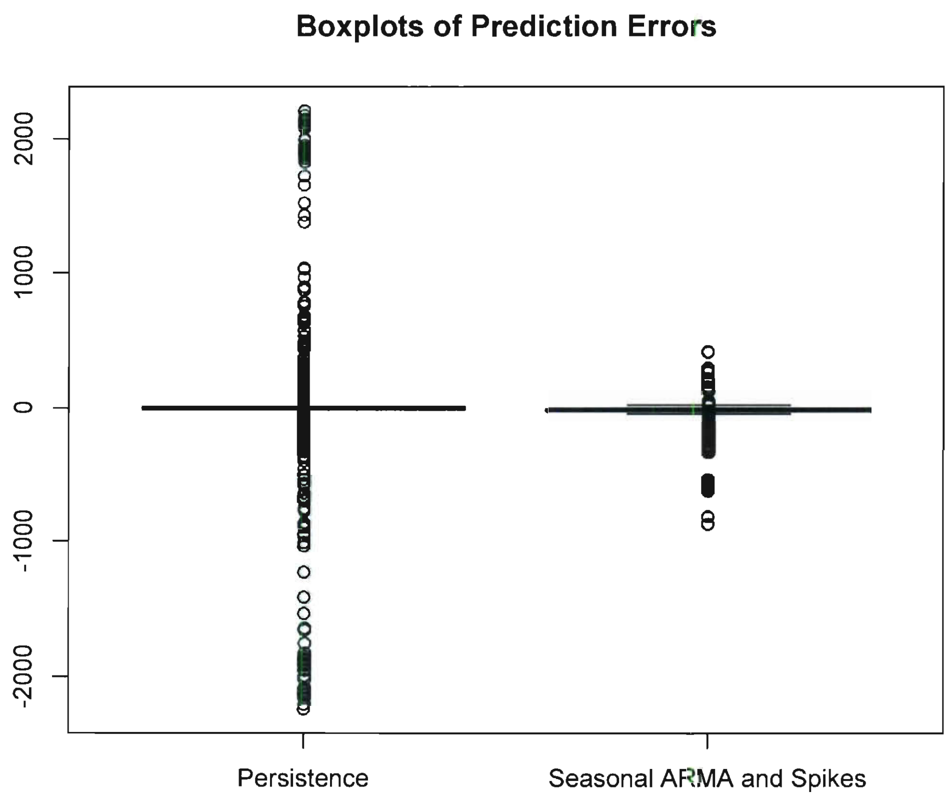


Figure 3.12 : Boxplots of the prediction errors for the Persistence model (MSPE = 73.1337) and the Mixture model (MSPE = 35.7021).

Figures 3.14, 3.13, 3.15, 3.16, 3.17 and 3.18 show the resampled coefficient estimates.

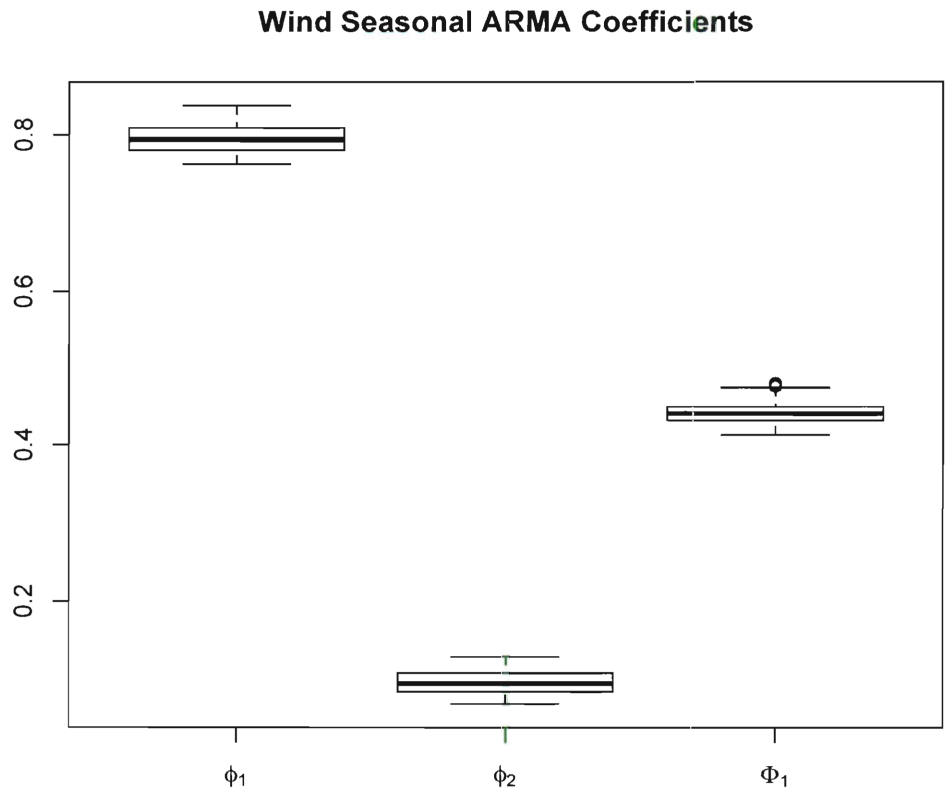


Figure 3.13 : Wind ARMA Coefficients

We can conclude that the starting point in the year does not have a dramatic affect on the parameter estimates, which was the desired result.

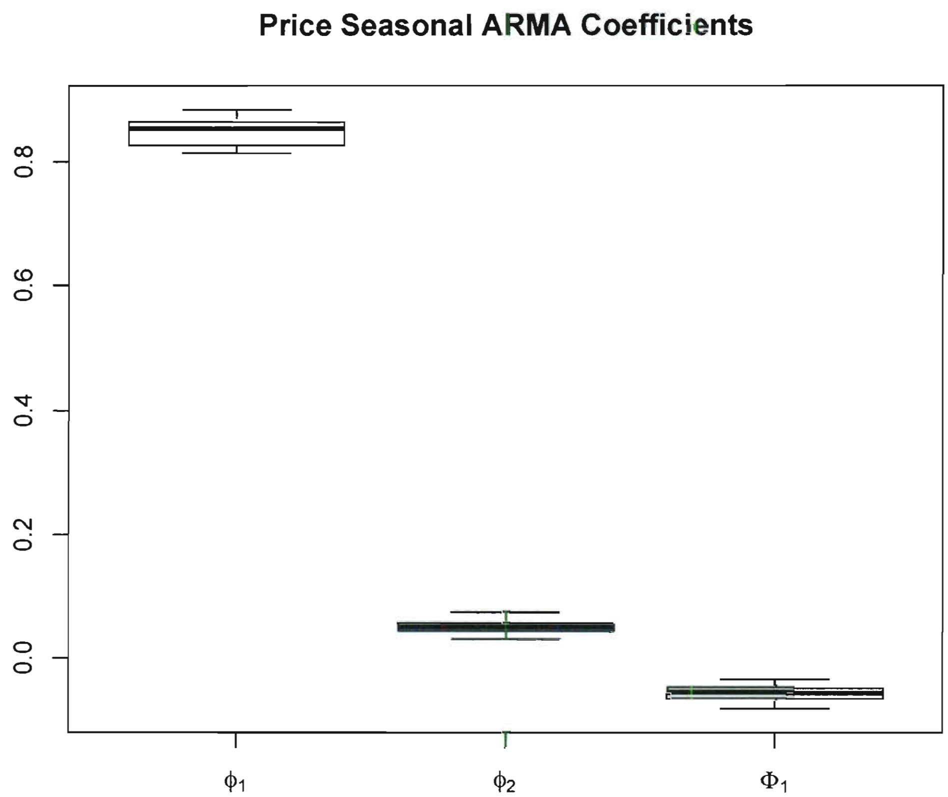


Figure 3.14 : Price ARMA Coefficients

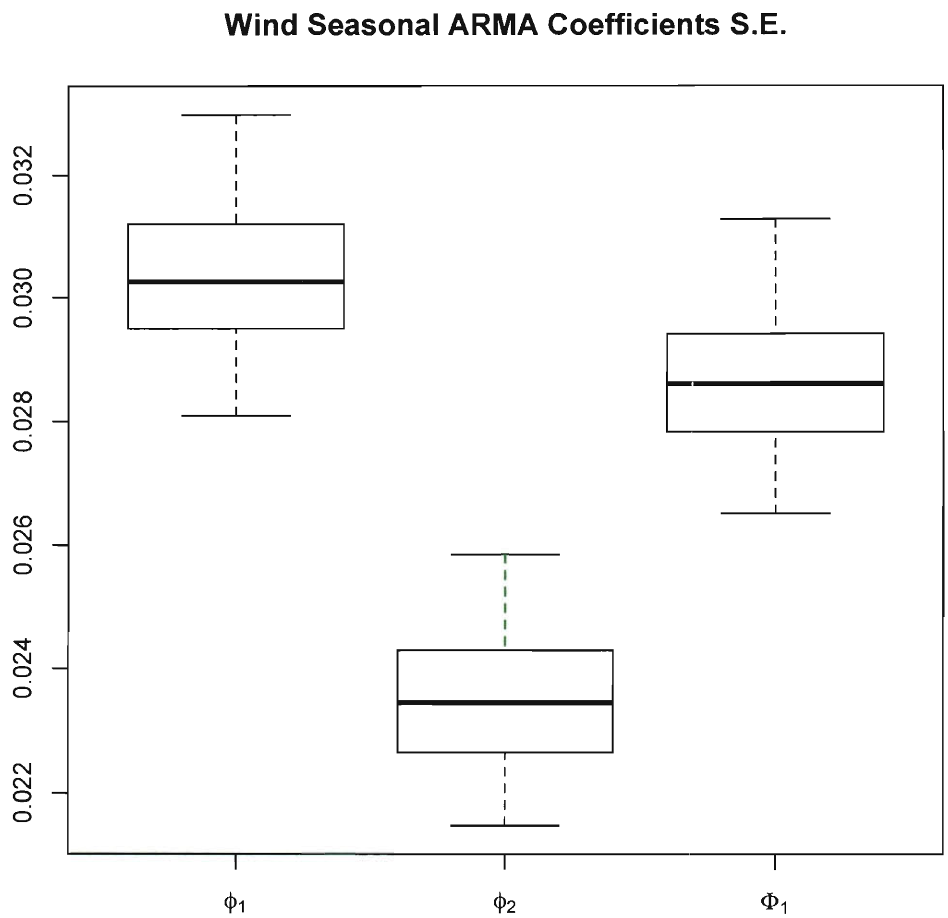


Figure 3.15 : Wind ARMA Coefficient Standard Errors

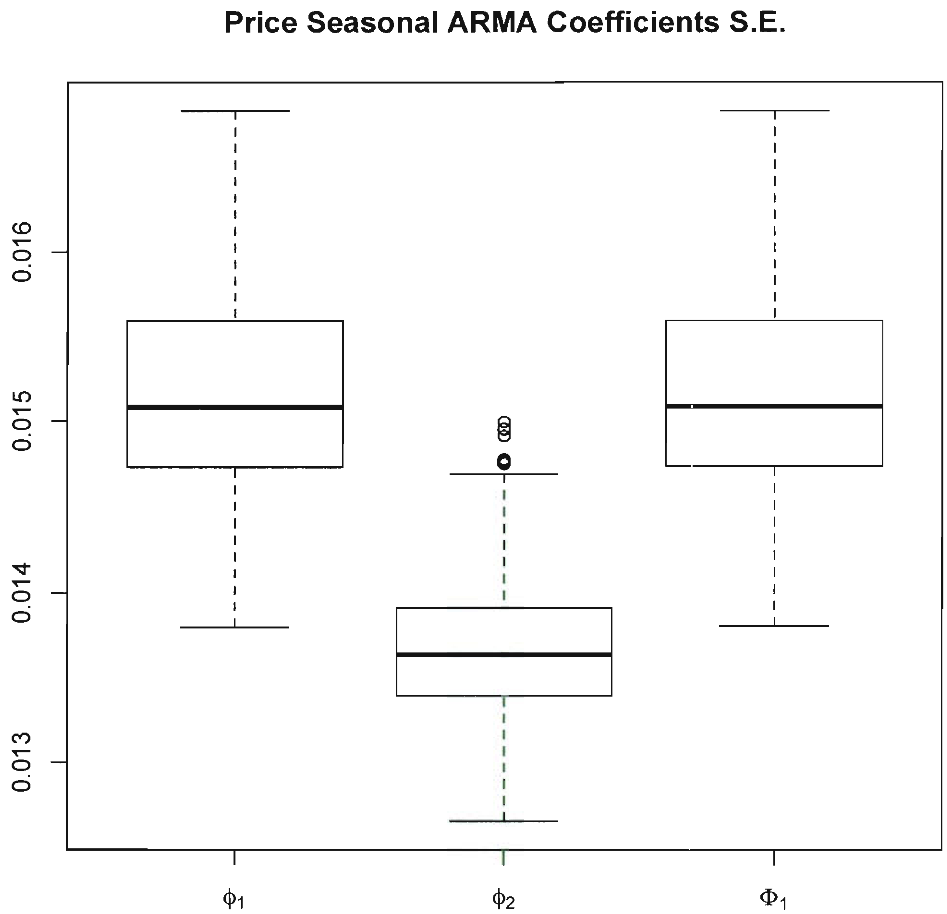


Figure 3.16 : Price ARMA Coefficient Standard Errors

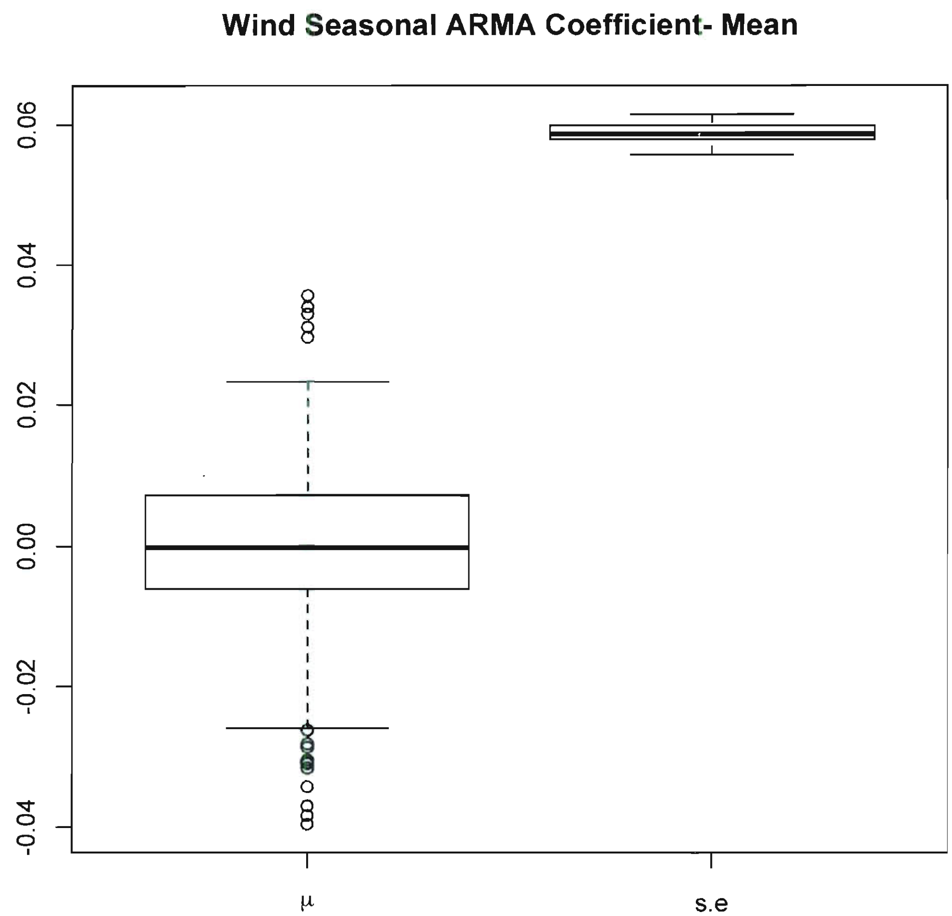


Figure 3.17 : Wind ARMA Mean

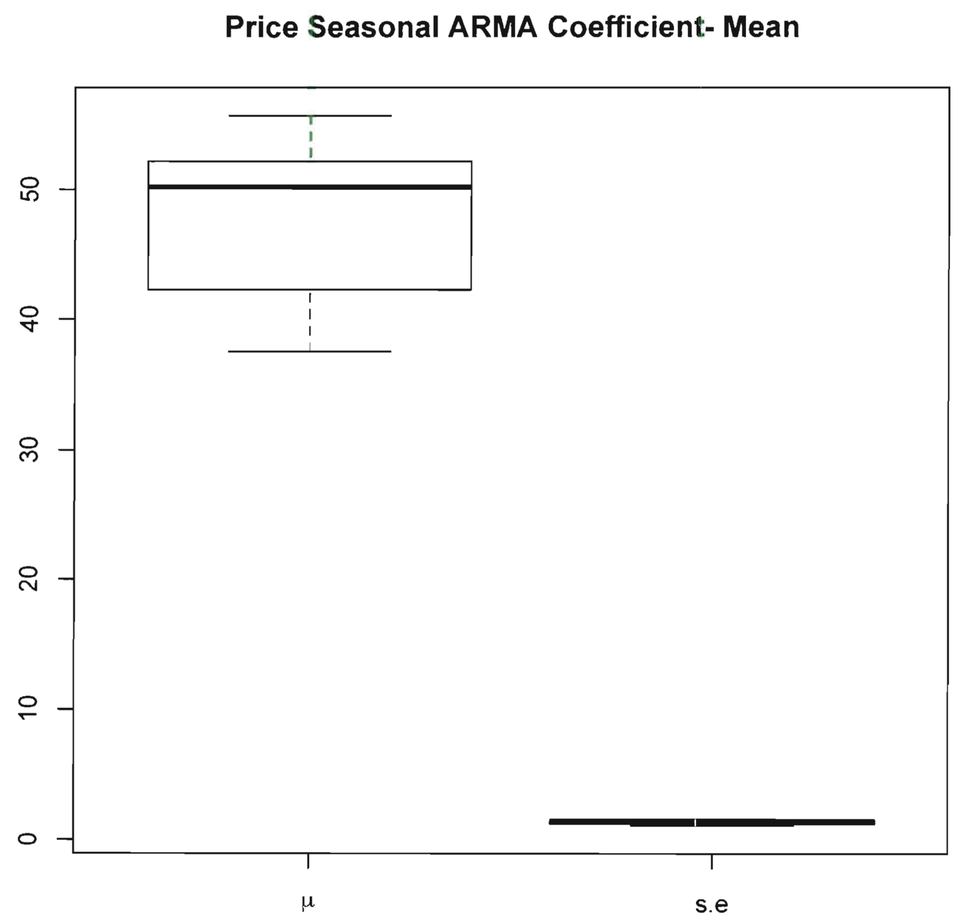


Figure 3.18 : Price ARMA Mean

# Chapter 4

# Revenue

## 4.1 Formulation of the Problem

Over the past ten years, with the increase in installed wind capacity, forecasting of both wind generation and power prices have been receiving an increased amount of attention. This is due to the fact that these predictions may be used in decision making by both wind farm owners but also by ERCOT, or any ISO to use wind generation more efficiently.

We look at the problem from the standpoint of the wind farm owner. We want to use our predictions of future prices and future wind production to come up with a bidding strategy for our output. As a wind farm we submit a bid to ERCOT for the amount of wind power. The following set up will allow us to determine an optimal bid. We follow similar notation to (Pinson *et al.* , 2007b) to sent up the revenue model.

For every program time unit (PTU), a market participant, in our case the wind farm, has to propose a level of contracted energy $E^c_{t+k}$. The $t+k$ subscript corresponds to a lead time where bids are proposed at time $t$. The revenue $R_{t+k}$ of a market participant proposing an amount of energy $E^c_{t+k}$ but actually generating $E^*_{t+k}$ can be expressed as:

$$R_{t+k} = \pi^c_{t+k} E^c_{t+k} + T^c_{t+k} \tag{4.1}$$

where $\pi^c_{t+k}$ is the contract price for this PTU, and $T^c_{t+k}$ is the imbalance cost on the balancing services market. An imbalance occurs when the amount of energy contracted is different from the amount of energy actually produced. Therefore, $d^*_{t+k}$ is defined as:

$$d^*_{t+k} = E^*_{t+k} - E^c_{t+k} \tag{4.2}$$

and it then follows that the imbalance cost, $T^c_{t+k}$ can be written as:

$$T^c_{t+k} = \begin{cases} \pi^{s,+}_{t+k} d^*_{t+k} & \text{if } d^*_{t+k} \geq 0, \\ \pi^{s,-}_{t+k} d^*_{t+k} & \text{if } d^*_{t+k} < 0. \end{cases} \tag{4.3}$$

where we define $\pi^{s,+}_{t+k}$ and $\pi^{s,-}_{t+k}$ as the imbalance prices for positive and negative imbalances respectively. The imbalance prices are a function of the spot price, $\pi^s_{t+k}$, at time $t+k$.

We next note that we can reformulate Equation 4.1 such that the revenue to the market participant for PTU $t+k$ is a combination of the income from selling actual wind generation, $E^*_{t+k}$, at the spot price, minus the costs of imbalance, given by .

$$R_{t+k} = \pi^c_{t+k} E^*_{t+k} - T^*_{t+k} \tag{4.4}$$

where

$$T^*_{t+k} = \begin{cases} \pi^+_{t+k} d^*_{t+k} & \text{if } d^*_{t+k} \geq 0, \\ \pi^-_{t+k} d^*_{t+k} & \text{if } d^*_{t+k} < 0. \end{cases} \tag{4.5}$$

The imbalance unit costs for positive and negative imbalances are $\pi^{+}_{t+k}$ and $\pi^{-}_{t+k}$, respectively. These are readily found from the contract prices and the imbalance prices as follows:

$$\pi^{+}_{t+k} = \pi^{c}_{t+k} - \pi^{s,+}_{t+k} \tag{4.6}$$

$$\pi^{-}_{t+k} = \pi^{s,-}_{t+k} - \pi^{c}_{t+k}. \tag{4.7}$$

The formulation of revenue in Equation 4.4 is made up of two terms, the first term is the income one would receive if using perfect predictions of energy produced. The contracted energy only appears in the second term, so the problem of maximizing revenue is equivalent to minimizing the costs of imbalance $T^{*}_{t+k}$.

We can define the imbalance $d_{t+k}$ as a random variable representing the difference between the random variable $E_{t+k}$ and the level of contracted energy $E^{c}_{t+k}$.

$$d_{t+k} = E_{t+k} - E^{c}_{t+k} \tag{4.8}$$

$E_{t+k}$ is a random variable for the amount of energy actually produced at time $t + k$. We denote an instance of the random variable, $E_{t+k}$, $E^{*}_{t+k}$, or the realized generation at time $t + k$ and it follows that $d^{*}_{t+k}$is a realization of that random variable $d_{t+k}$.

Looking at this from the standpoint of a wind farm owner, we want to maximize our revenue. Following the formulation in Equation 4.4, this equates to minimizing the loss function associated to regulation costs.

The required properties of a loss function are discussed in Granger (1999). In order to be considered a loss function, $g$, must fulfill the following:

A) $g(0) = 0$, i.e. if there is no error there is no loss

B) $min_e g(e) = 0$, i.e. $g(e) \geq 0$

C) $g(e)$ is monotonically non-decreasing as $e$ moves away from zero so that $g(e_1) \geq g(e_2)$ if $e_1 > e_2 > 0$ and if $e_1 < e_2 < 0$.

We define the loss function, $g$, is to consider that the loss is directly given by the regulation unit costs $\pi_{t+k}^{*,+}$ and $\pi_{t+k}^{*,-}$ (Pinson *et al.* , 2007b). They define the slope of linear functions for positive and negative values of $d$ as follows:

$$g : d^* \rightarrow \begin{cases} \pi_{t+k}^{+} d^* & \text{if } d^* \geq 0, \\ -\pi_{t+k}^{-} d^* & \text{if } d^* < 0. \end{cases} \tag{4.9}$$

The regulation unit costs, $\pi_{t+k}^{+}$ and $\pi_{t+k}^{-}$, are not known at the time of bidding, so they must be replaced with forecasts or estimates, $\hat{\pi}_{t+k}^{+}$ and $\hat{\pi}_{t+k}^{-}$, in Equation 4.9.

To now determine the optimal bid, we follow these steps:

- Given a one step ahead (or 15 minute) prediction of the positive and negative imbalance prices, $\hat{\pi}_k^{+}$ and $\hat{\pi}_k^{-}$ at each PTU

- Given a one step ahead predictive distribution, $\hat{F}_{t+k}^{E}$ of the wind output at each PTU

- The optimal bid strategy for a utility maximizing scheme is

$$\begin{aligned}
\tilde{E}^{C}_{t+k} &= arg\ min_{E^{C}_{t+k}} \mathbb{E}[g(d_{t+k})] \\
&= arg\ min_{E^{C}_{t+k}} \mathbb{E}[T^{*}_{t+k}] \\
&= {G^{E}_{t+k}}^{-1} \left( \frac{\hat{\pi}^{+}_{k}}{\hat{\pi}^{+}_{k} + \hat{\pi}^{-}_{k}} \right)
\end{aligned} \tag{4.10}$$

where $G^{E}_{t+k}$ is the cdf for $E_{t+k}$, and is estimated from $\hat{F}^{E}_{t+k}$.

## 4.2 Analysis

In the past, this economic model has been used for analysis of the Denmark Nord Pool electricity market (Pinson *et al.* , 2007b). In this paper, they assume that the best estimate of the positive and negative imbalance price series is an annual trend. In the case of ERCOT, we can forecast the marginal clearing price for energy (MCPE), of which the imbalance price is a fraction. Given our predictions of the price series, we have predictions of the imbalance price series that is much more informative than an annual trend. We assert that using these price predictions, rather than an annual trend will lead to a different outcome in the energy we should place under contract, which in turn will increase revenue to the wind farm owner.

We make several assumptions. We are interested in short term predictions, so we assume that wind farms participate in balancing energy services. While this is currently not the case in ERCOT, it is in many other ISOs, and may be true in the near future. We also assume, as do (Pinson *et al.* , 2007b) that wind farms do not apply control strategies. This means that wind farms run when they have wind to turn the turbines and do not run when they do not have wind. This assumption was true until recently. Older wind turbines did not have the capability to turn off if the wind was blowing, but more technologically advanced models now allow wind farms to monitor prices and turn off the turbines if desired.

Recall, the data we used to predict wind generation is an aggregate of all wind farms in West Texas. To assess how the accuracy of those predictions as well as the predictions of price affect wind farm revenue, we imagine that all of the wind farms are owned and operated by one company, and that this company is able to submit bids for electricity 1 hour in advance (this is what generation does in the balancing energy market). We also assume that the bid is accepted by ERCOT. This should be the case because Wind generation has a lower cost of fuel than traditional generation.

The definition of the loss function in Equation 4.9 is consistent with the way ERCOT ascribes imbalance costs to wind farms in the new nodal system. Rules regarding wind generation have changed every six months in ERCOT, but currently, when wind farms under or over produce, they are required to purchase replacement energy. Under generation is not subjected to any additional imbalance costs so $\pi_{t+k}^{s,-} = \pi_{t+k}^{s}$ (Sioshansi & Hurlbut, 2009). Over generation is subject to an additional deviation penalty according to $\pi_{t+k}^{s,+} = \pi_{t+k}^{s}(1+\tau)$. Where $\tau$ is set by ERCOT.

$$\tau = min(1.0, \frac{1 - tolerance}{max\ tolerance - tolerance}) \tag{4.11}$$

ERCOT has set the *max tolerance* at 125MW. We make a simplifying assumption that the *tolerance* is 0. While this may not always be the case (generally there is a small percentage of deviation from contracted energy allowed before a deviation cost is incurred), we must make this assumption in order to allow the deviation cost to be independent of the contracted energy amount, $E^c_{t+k}$. When we make this simplifying assumption, we can then calculate that $\tau = \frac{1}{125}$.

Figure 4.1 shows a sample loss function. The loss function has as slopes the unit imbalance costs $\pi^+_{t+k}$ and $\pi^-_{t+k}$.

Table 4.1 below shows the revenue from wind farms in ERCOT using the various prediction methods shown previously. We see that by using an ARMA + ACD model for the prices and a seasonal ARMA model for the wind prediction, that we are indeed able to produce more revenue using the more accurate prediction methods. We also note that in all methods of wind prediction, we are able to greatly increase the revenue when we use our ARMA + ACD model for price prediction and vice versa. Figure 4.2 shows the resampled revenue results for three cases: persistence + persistence, seasonal arma + seasonal arma and ACD, and perfect + perfect. We see that the revenue improvement does not depend on the starting point in the year.

| | | Price Model | | |
|---|---|---|---|---|
| | | Persistence | ARMA + ACD | Perfect |
| | Persistence | .35 | .39 | .41 |
| Wind Model | Seasonal ARMA | .38 | .47 | .49 |
| | Perfect | .40 | .56 | .68 |

Table 4.1 : Revenue improvement to wind farm Sept 13 - Dec 31, 2008, in Billions of dollars

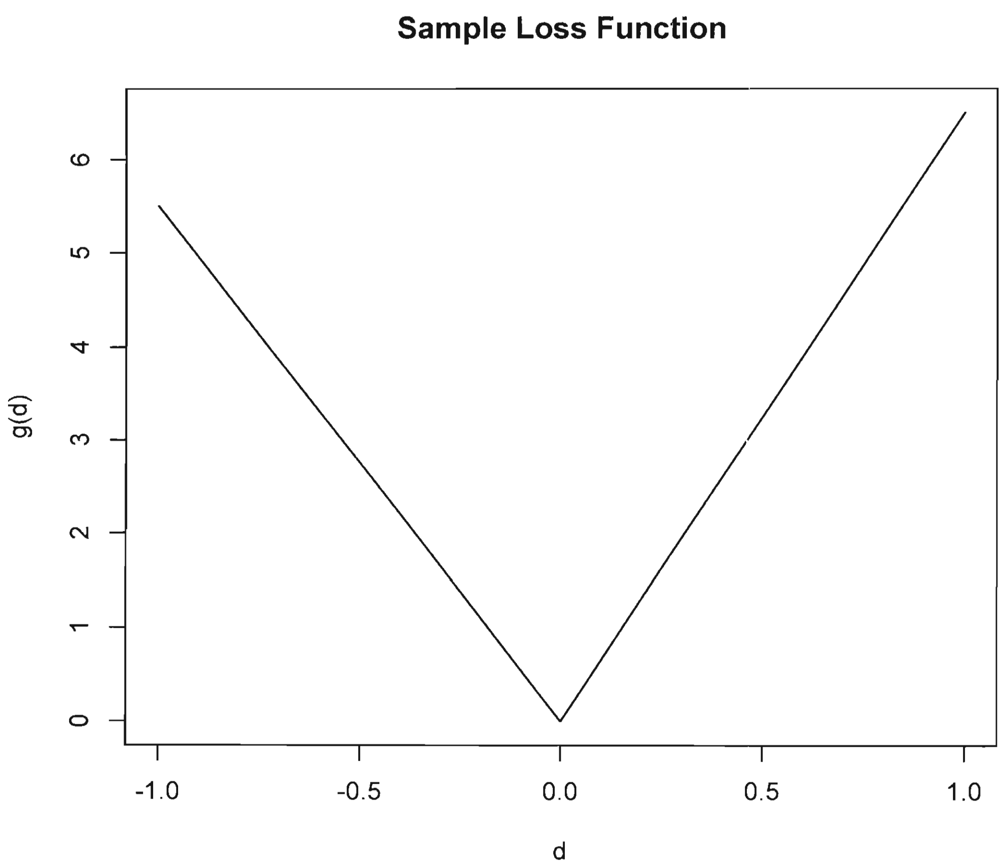


Figure 4.1 : Sample Loss Function for a given time $t$. Slopes based on imbalance unit costs.

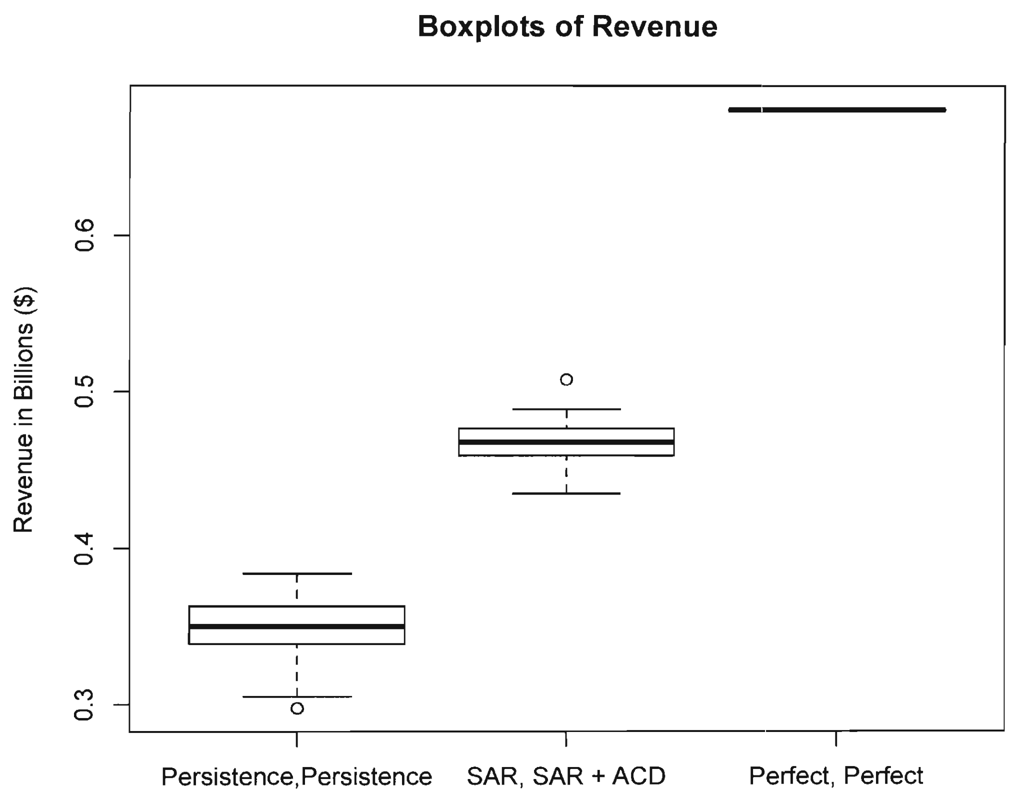


Figure 4.2 : Revenue Improvement Achieved Using Model Each for Wind and Prices

# Chapter 5

# Conclusions

Wind is, and will continue to be a challenge to electricity grids. Future plans include more 20,000 MW of generation by 2013 in Texas alone. Denmark is able to generate over 20% of energy from wind farms, and the U.S. (along with several other countries) would like to follow suit. Using more accurate prediction techniques allow wind farms to be used more efficiently on the grid. ERCOT can use probabilistic forecasts of wind generation to determine the amount of wind they will allow to be used as generating reserves. Currently that number is 8.7% of installed capacity, but this number could go up in the future if the accuracy of forecasting used by ERCOT is improved.

Recently, ERCOT issued the following statement about wind power. "With the increased percentage of the system load served by wind, it becomes critical to have not only a good forecast of how wind will generate during the day, but also an assessment of the level of uncertainty in that forecast," Saathoff said. "Since we don't have much control over wind, the key for grid reliability is to have a good wind forecast, and be prepared for the variability of wind as we are for load, rather than as a controllable capacity resource," Saathoff said. (ERCOT, 2010) This further supports our theory that we need more accurate prediction methods because wind will be part of the future of the power grid.

In this dissertation, we show that using time series forecasting methods which include price spike prediction allows wind farms to contract different levels of energy than one would find from using a model that ignores spikes. We are able to improve upon persistence forecasts mean squared prediction error by 48%. This difference in contracted energy levels leads to a higher revenue for the wind farm. Our comparison is especially important in the price prediction series. We used the same wind generation prediction model and noted how our revenue changed with an increased prediction accuracy on the price series. Our prediction of wind generation also results in an increased revenue for a fixed method of price prediction, but this is to a lesser extent than we see for price prediction. Our proposed set of prediction tools leads to a 38% increase in revenue. However, in the future, this work can be applied to a particular wind farm, and in this case, we will see more volatile wind generation and the prediction of spikes in this time series will be vitally important.

In the future, we plan to investigate the use of this model for individual nodes on the ERCOT grid. Recall, the ERCOT grid will operate at the node level effective December 1, 2010. When looking at an individual node, or individual wind farm, we can apply the ACD models used in price prediction to predict ramp events that were not visible on the grid level. Finally, we would like to investigate the application of the ACD model to predict unplanned outages on the grid, and the increase in revenue that could follow from this prediction.

# A : Notation

$t$ - Time at which the contract is created

$t + k$ - Time in the future for which the contracted energy is to be delivered

$R_{t+k}$- Revenue of Wind Farm at time $t + k$

$E^c_{t+k}$- Level of Contracted Energy (MWh)

$E^*_{t+k}$- Realized Generation at time $t + k$

$\hat{E}_{t+k}$- Forecasted Generation at time $t + k$

$T^c_{t+k}$- Imbalance Cost

$T^*_{t+k}$- Realized Imbalance Cost

$\pi^c_{t+k}$- Contract Price

$\pi^s_{t+k}$- Spot Price (Balancing Energy Price at time $t + k$)

$d_{t+k}$- System Imbalance

$d^*_{t+k}$- Realized System Imbalance

$\pi^{s,+}_{t+k}$, $\pi^{s,-}_{t+k}$- Positive and Negative Imbalance Prices

$\pi^+_{t+k}$, $\pi^-_{t+k}$- Positive and Negative Unit Imbalance Prices

$\hat{\pi}^+_{t+k}$, $\hat{\pi}^-_{t+k}$- Forecasted Positive and Negative Unit Imbalance Prices

# B : Proof

The proof for Equation (12) is as follows:

Maximizing the expected revenue:

$$
\begin{aligned}
\mathbb{E}[R_{t+k}] &= \mathbb{E}[\pi^C_{t+k}E^*_{t+k} - T^*_{t+k}] \\
&= \int_0^{E^C_{t+k}} (\pi^C_{t+k}x + \pi^{*,-}_{t+k}(x - E^C_{t+k}))F^E_{t+k}(x)dx \\
&\quad + \int_{E^C_{t+k}}^1 (\pi^C_{t+k}x - \pi^{*,+}_{t+k}(x - E^C_{t+k}))F^E_{t+k}(x)dx
\end{aligned}
$$

Taking the derivative,

$$
\begin{aligned}
\frac{\partial}{\partial x}\mathbb{E}[R_{t+k}] &= [E^C_{t+k}\pi^C_{t+k} + (E^C_{t+k} - E^C_{t+k})\pi^{*,-}_{t+k}]F^E_{t+k}(E^C_{t+k}) \\
&\quad + \int_0^{E^C_{t+k}} \pi^{*,-}_{t+k}F^E_{t+k}(x)dx \\
&\quad - [E^C_{t+k}\pi^C_{t+k} - (E^C_{t+k} - E^C_{t+k})\pi^{*,+}_{t+k}]F^E_{t+k}(E^C_{t+k}) \\
&\quad - \int_{E^C_{t+k}}^1 \pi^{*,+}_{t+k}F^E_{t+k}(x)dx
\end{aligned}
$$

Setting equal to 0,

$$
\begin{aligned}
0 &= \pi^{*,-}_{t+k} \int_0^{E^C_{t+k}} F^E_{t+k}(x)dx - \pi^{*,+}_{t+k} \int_{E^C_{t+k}}^1 F^E_{t+k}(x)dx \\
0 &= \pi^{*,-}_{t+k} G^E_{t+k}(E^C_{t+k}) - \pi^{*,+}_{t+k}(1 - G^E_{t+k}(E^C_{t+k})) \\
\pi^{*,+}_{t+k} &= (\pi^{*,-}_{t+k} + \pi^{*,+}_{t+k}) G^E_{t+k}(E^C_{t+k}) \\
\frac{\pi^{*,+}_{t+k}}{\pi^{*,-}_{t+k} + \pi^{*,+}_{t+k}} &= G^E_{t+k}(E^C_{t+k}) \\
\tilde{E}^C_{t+k} &= {G^E_{t+k}}^{-1}\left(\frac{\pi^{*,+}_k}{\pi^{*,+}_k + \pi^{*,-}_k}\right) \quad \square
\end{aligned}
$$

(Bremnes, 2004) (Pinson *et al.* , 2007b) (Granger, 1999)

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